Potsdam Institute for Climate Impact Research

Allowance prices in the EU ETS

- price drivers and the recent upward trend -

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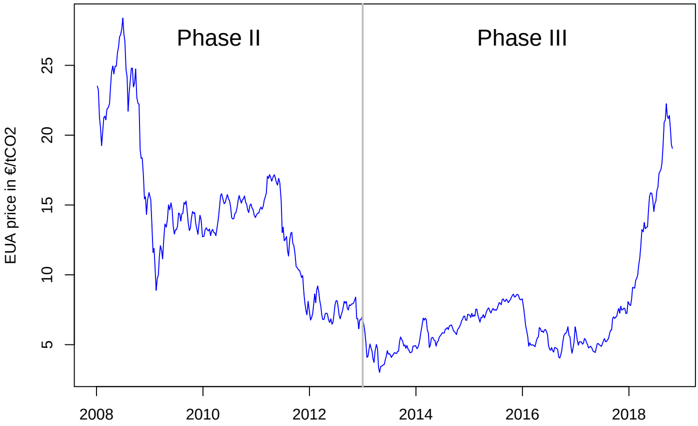
Leibniz-Gemeinschaft

Development of EUA prices in Phases II and III



EUA December futures from Jan 2008 to Oct 2018

EU ETS empirical (price drivers) literature

- **Theory**: most important price drivers are *coal prices (-)* and *gas prices (+)*. Potentially, economic activity/oil prices *(+)*, weather variables *(+)* and renewables *(-)*
- **Practice**: hard to find empirical evidence
- Previous studies:
  - ✓ find insignificant coefficient of coal (e.g. Hintermann (2010), Koch et al. (2014))
  - ✓ split the sample in parts, include dummy variables
  - ✓ find a positive and significant effect of gas
  - ✓ allow for different pricing regimes (Lutz et al. (2013))
  - ✓ find positive effect of coal (Lutz et al. (2013), Rickels et al. (2014))
- so far, no paper has looked empirically at the *recent upward trend*

Our analysis - Overview

- Step 1: fundamental price drivers
  - ✓ a possible explanation for previous findings might be an unstable relationship between the allowance price and its fundamental drivers
  - ✓ we look at the relationship in a time-varying regression approach
  - ✓ we find evidence of time variation in the coefficients
  - ✓ hypothesis: fundamentals become more relevant drivers when allowances get scarce(r)?

- Step 2: testing for *explosive* behavior
  - ✓ we empirically investigate the recent upward trend with the help of Phillips, Shi and Yu (2015)'s "bubble detection test"
  - ✓ we find clear evidence of unusual, *explosive* behavior

Step 1: Price drivers

- we use the following model:

$$r_{EUA,t} = \beta_{0,t} + \beta_{1,t}x_{1,t} + \beta_{2,t}x_{2,t} + \cdots + \beta_{m,t}x_{m,t} + \epsilon_t,$$

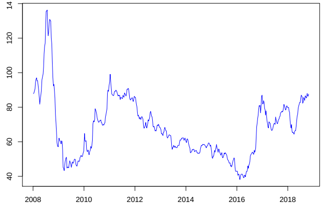
- $x_{j,t}$ (for $j = 1, \ldots, m$) represent the stationary price drivers
- we consider (a) $\beta_{j,t} = \beta_j$ and (b) $\beta_{j,t} = \beta_j(t)$
- estimation in (a) OLS, in (b) **nonparametric kernel methods**
- 95% confidence intervals in (b) obtained using an **autoregressive wild bootstrap** approach

$\Longrightarrow$ flexible, time-varying approach, robust to serial correlation and heteroskedasticity

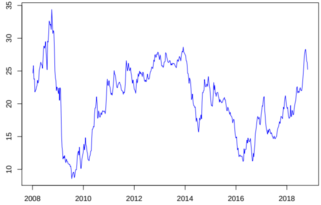
The Data

- $y_t = EUA_t$ (Emission Allowances, Dec Futures from EEX)
- $\mathbf{x}_t = \{coal_t, gas_t, oil_t, stocks_t, temperature_t\}$
  - ✓ month-ahead coal futures (API2)
  - ✓ month-ahead gas futures (TTF)
  - ✓ month-ahead oil futures (Brent)
  - ✓ Euro STOXX50/STOXX600 index
  - ✓ temperature data from ECA&D
- weekly data from January 2008 to October 2018
  - ✓ Phases II and III
- $>$500 observations
- results are obtained using returns rather than price data due to nonstationarity

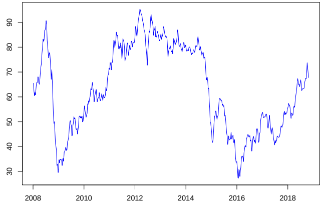
The Data



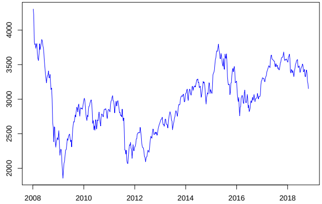
(a) Coal



(b) Gas

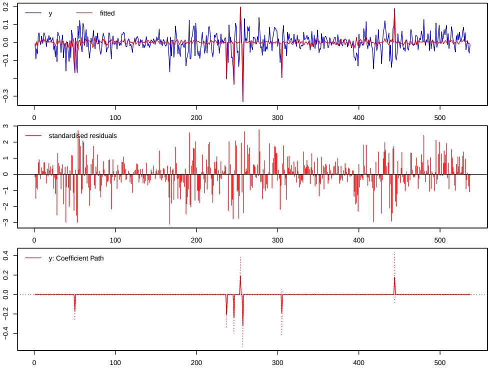


(c) Oil



(d) Stoxx 50

Results - Outlier Detection



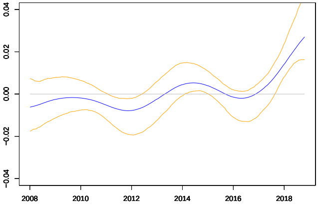
Impulse Indicator Saturation (IIS) approach detects 7 outliers
(Jan 2009, Nov 2012, Jan 2013, Mar and Apr 2013, Mar 2014, Dec 2016)

Linear Regression

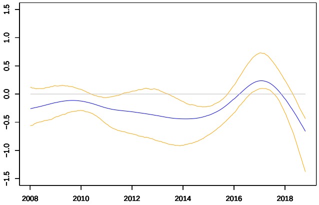
OLS regression results									
	(1)			(2)			(3)		
	$\hat{\beta}_j$	se_{NW}	p-value	$\hat{\beta}_j$	se_{NW}	p-value	$\hat{\beta}_j$	se_{NW}	p-value
Coal	-0.119	0.094	0.206	-0.061	0.097	0.528	-0.07	0.097	0.425
Gas	0.190	0.075	0.012	0.198	0.074	0.007	0.198	0.074	0.008
Oil	0.214	0.069	0.002	–	–	–	–	–	–
Temp	-0.001	0.001	0.572	-0.001	0.001	0.450	-0.001	0.001	0.451
Stoxx 50	–	–	–	0.139	0.103	0.031	–	–	–
Stoxx 600	–	–	–	–	–	–	0.296	0.110	0.007

Table: Linear regression results. The dependent variable is the return on EUAs and the set of (stationary) regressors changes in each specification. The standard errors are of the Newey-West type.

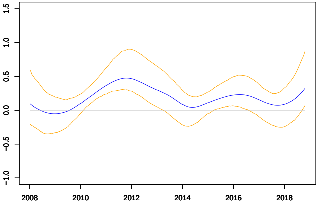
Results - Time-varying coefficients



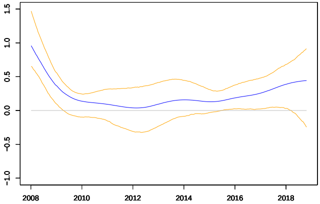
(e) Trend



(f) Coal



(g) Gas



(h) Oil

Step 2: The recent upward trend

- we use the recently developed **right-sided unit root tests** by Phillips, Shi and Yu (2015)
- H_0: unit root ($\beta = 0$) vs. H_1: explosive behavior ($\beta > 0$)
- based on the regression model, for $t \in [\lfloor r_1 T \rfloor, \lfloor r_2 T \rfloor]$

$$\Delta y_t = \alpha_{r_1,r_2} + \beta_{r_1,r_2} y_{t-1} + \sum_{j=1}^{k} \phi_{r_1,r_2}^{j} \Delta y_{t-j} + \epsilon_t,$$

- the tests compare $\text{ADF}_{r_1}^{r_2}$ statistics on a forward and backward expanding window (GSADF)
  - ✓ **G**eneralized **S**upremum **A**ugmented **D**ickey-**F**uller test
- date stamping: calculate for every end point r_2 (BSADF_{r_2})
  - ✓ **B**ackward **S**upremum **A**ugmented **D**ickey-**F**uller test

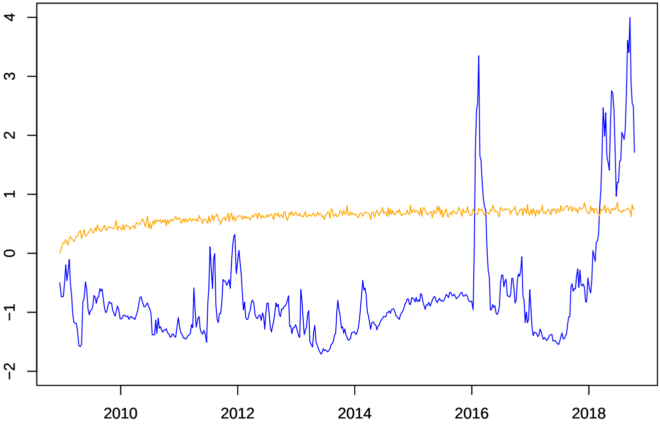
Results - GSADF Tests

GSADF tests			
Test statistics		Critical values (90%, 95%, 99%)	
Series	GSADF	simulated	bootstrap
EUA	3.998	(1.983, 2.175, 2.608)	(2.270, 2.555, 3.201)
Coal	1.676		(2.487, 2.795, 3.446)
Gas	1.299		(2.383, 2.645, 3.372)
Oil	2.722		(2.200, 2.505, 3.104)
Stoxx 50	0.782		(2.310, 2.668, 3.099)
Stoxx 600	0.953		(2.302, 2.302, 3.170)

Table: The GSADF test statistics with simulated critical values (2000 repetitions) and bootstrapped critical values (5000 repetitions).

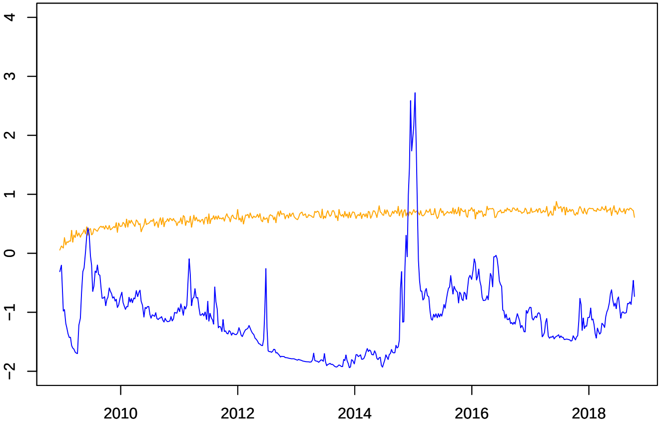
$\Longrightarrow$ unit root null hypothesis rejected for EUA and oil price series

Results - Date Stamping - BSADF Test EUA



test statistics (blue) – critical values (orange)

Results - Date Stamping - BSADF Test Oil



test statistics (blue) – critical values (orange)

Step 2 - Summary

- The test detects an ongoing period of exuberance in line with the recent upward trend, starting in March 2018
- This is by far the longest of such periods found by the test
- Previous study looks at daily data from 2005 to 2014 and finds explosive periods to last at most a few days (Creti and Joëts (2017))
- Test detects no simultaneous explosive behavior in fundamental price drivers

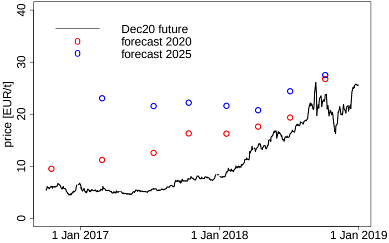
Overall Summary

- we look at the effect of the classical price drivers of EUA prices
- we find time variation and/or periods of insignificance
- we also find a significant (unexplained) upward trend since the end of 2017
- a formal test provides evidence of ongoing explosive behavior
- fundamentals do not seem to provide an explanation for this
- adaptation to new equilibrium price level that can appear explosive (Harvey et al. 2016), or overreaction to reform leading to a speculative bubble?

Contagious stories?

- many bubble-generating mechanisms identified in behavioral finance literature, including contagious stories
  - ✓ "*rapid price increases boost the contagion rate of popular stories justifying that increase, heightening demand and more price increases*" (Shiller 2017)
  - ✓ "*EUAs are structurally bullish [due to MSR], just waiting for [...] any story that reinforces the argument.*" (CarbonPulse)

- analysts forecasts about reform impacts as contagious stories?



References I

Creti, A. and Joets, M. (2017). Multiple bubbles in the European Union Emission Trading Scheme. Energy Policy, 107:119-130.

Harvey, D. I., Leybourne, S. J., Sollis, R., and Taylor, A. M. R. (2016). Tests for explosive financial bubbles in the presence of non-stationary volatility. Journal of Empirical Finance, 38:548-574.

Hintermann, B. (2010). Allowance price drivers in the first phase of the EU ETS. Journal of Environmental Economics and Management, 59(1):43-56.

Koch, N., Fuss, S., Grosjean, G., and Edenhofer, O. (2014). Causes of the EU ETS price drop: Recession, CDM, renewable policies or a bit of everything?-New evidence. Energy Policy, 73:676-685.

References II

Lutz, B. J., Pigorsch, U., and Rotfuss, W. (2013). Nonlinearity in cap-and-trade systems: The EUA price and its fundamentals. Energy Economics, 40:222-232.

Phillips, C.B., Shi, S., Yu, J. (2015). Testing for multiple bubbles: Historical episodes of exuberance and collapse in the S&P 500. International Economic Review 56(4):1043-1078.

Backup - Estimation

- estimation is performed using nonparametric, local linear kernel estimator (Cai (2007)) $\widehat{\boldsymbol{\theta}} = (\widehat{\beta} \quad \widehat{\beta}^{(1)})'$

$$\widehat{\boldsymbol{\theta}}(\tau) = \begin{pmatrix} \mathbf{S}_{n,0}(\tau) & \mathbf{S'}_{n,1}(\tau) \\ \mathbf{S}_{n,1}(\tau) & \mathbf{S}_{n,2}(\tau) \end{pmatrix}^{-1} \begin{pmatrix} \mathbf{T}_{n,0}(\tau) \\ \mathbf{T}_{n,1}(\tau) \end{pmatrix},$$

- where for $k = 0, 1, 2$:

$$\mathbf{S}_{n,k}(\tau) = \frac{1}{n} \sum_{t=1}^{T} \mathbf{x}_t \mathbf{x}_t' \left(\frac{t}{n} - \tau \right)^k K_h \left(\frac{\frac{t}{n} - \tau}{h} \right)$$

$$\mathbf{T}_{n,k}(\tau) = \frac{1}{n} \sum_{t=1}^{T} \mathbf{x}_t \left(\frac{t}{n} - \tau \right)^k K_h \left(\frac{\frac{t}{n} - \tau}{h} \right) y_t$$

- confidence intervals are constructed with the help of autoregressive wild bootstrap

Backup - Bootstrap algorithm

Step 1 Calculate $\hat{u}_t = y_t - \mathbf{x}_t' \widehat{\boldsymbol{\theta}}(\tau)$

Step 2 For $0 < \gamma < 1$, generate $\nu_1^*, \ldots, \nu_n^*$ as i.i.d. $\mathcal{N}(0, 1-\gamma^2)$ and let

$$\xi_t^* = \gamma \xi_{t-1}^* + \nu_t^* \quad \text{with} \quad \xi_1^* \sim \mathcal{N}(0,1)$$

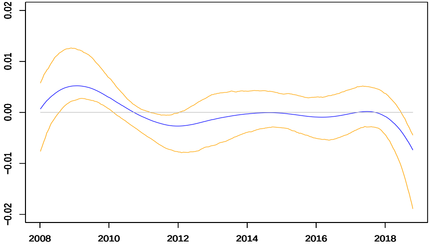
Step 3 Calculate the bootstrap errors u_t^* as $u_t^* = \xi_t^* \hat{z}_t$ and generate the bootstrap observations by

$$y_t^* = \mathbf{x}_t' \widehat{\boldsymbol{\theta}}(\tau) + u_t^*$$

Step 4 Repeat Steps 2 and 3 B times and apply the nonparametric estimator to obtain the quantiles

$$\hat{q}_{\alpha,j}(\tau) = \inf \left\{ u \in \mathbb{R} : \mathbb{P}^* \left[\hat{\beta}_j^*(\tau) - \hat{\beta}_j(\tau) \leq u \right] \geq \alpha \right\}$$

Results - Time-varying coefficients (temperature)



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$$GSADF(r_0) = \sup_{\substack{r_2 \in [r_0,1] \\ r_1 \in [0, r_2 - r_0]}} ADF_{r_1}^{r_2}$$

- Locating explosive periods, calculate for every end point r_2:

$$BSADF_{r_2}(r_0) = \sup_{r_1 \in [0, r_2 - r_0]} ADF_{r_1}^{r_2}$$