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Modelling and forecasting European Union allowance prices applying artificial neural networks

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JUNTA DE EXTREMADURA
Consejería de Educación y Empleo

GDAE
Global Development And Environment Institute at Tufts University

Research in progress

EU Emission Trading System (EU ETS) - 2005

Pollutant Companies must manage allowance costs

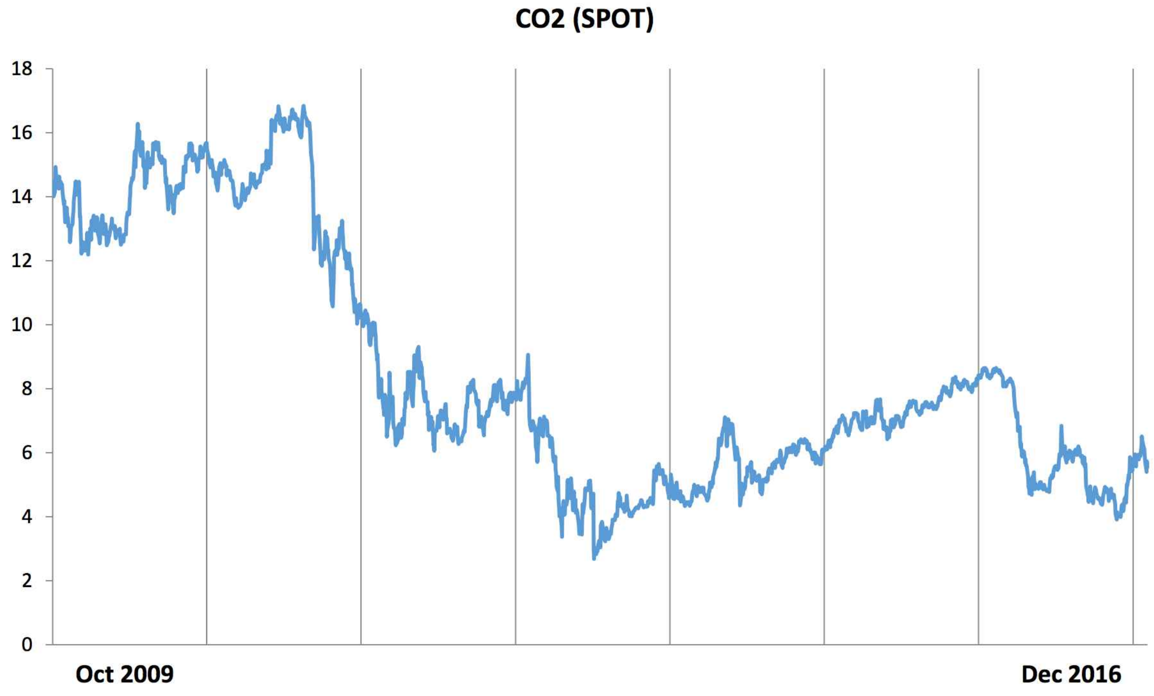
(power plants, oil refineries, ferrous metallurgy, cement clinker or lime, glass including glass fiber, ceramic products by firing, and pulp, paper and board)

- Carbon price predictions are important for the companies (production costs and decarbonization investments)
- Carbon prices can affect stock market returns.

Carbon price predictions

<u>EU Emission Trading System (EU ETS).</u>

- 2005-07: Trial period.
- 2008-12: 90% for free.
- 2013-20: auctioning from 20% up to 70%



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- It is important to forecast the EUA prices:
  → it can affect decarbonization investment decisions (Fuss & Szolgayová 2010, Shahnazari et al. 2011)
  → prices are critical for companies, brokers, traders and investors (Atsalakis, 2016)

- Allowance price is expected to be determined by the balance between supply and demand (Fezzi & Bunn, 2009)

- Literature has tried to identify the factors:
  Chevallier (2011), Lutz *et al*. (2013), Aatola *et al*. (2013), Oberndorfer (2009), Moreno & Pereira (2016)

- Atsalakis (2016): computational model (PATSOS) - “a novel tool to manage and evaluate environmental risks companies face because of EU related to carbon emissions”

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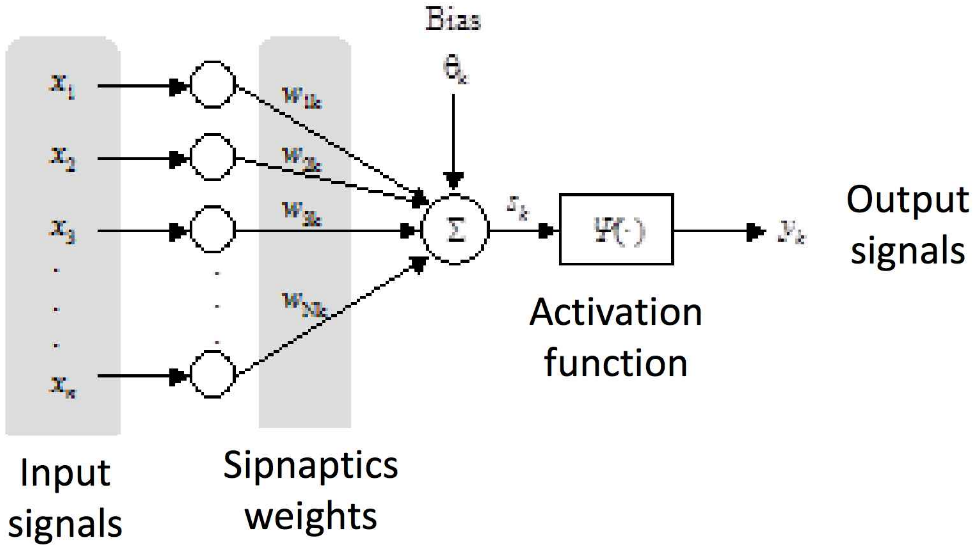
- Our paper tries to provide accurate forecasts for the carbon prices.

- Variables: Gas, oil, coal and electricity spot prices.

- Technique: artificial neural network system (mathematical models designed to emulate the human brain in solving problems).



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Variables

- Oct 2009-Dec 2016
- Daily: more than 22.000 data

Dependent VARIABLE _y	CO2 price	Future price	CO2_FUTUROS
Independent VARIABLES _X1	EUROPE PRICE INDEX Sectors included EU ETS	EUROPE-DS Electricity - PRICE INDEX EUROPE-DS Iron & Steel - PRICE INDEX EUROPE-DS Paper - PRICE INDEX EUROPE-DS Chemicals - PRICE INDEX EUROPE-DS Oil & Gas Prod - PRICE INDEX	SI_Electricity SI_Iron & Steel SI_Paper SI_Chemicals SI_OilGas
Independent VARIABLES _X2	FUELS prices	Natural Gas-Henry Hub $/MMBTU Crude Oil Dated Brent U$/BBL Coal ICE API2 CIF ARA Nr Mth $/MT - SETT. PRICE	P_gas P_Oil P_Coal

Correlation

- Iron and steel industries
- Power sector

' '	'PrecCO2'	'FutCO2'	'IndElec'	'IndIron'	'IndPap'	'IndChem'	'IndOil'	'PrecGas'	'PrecOil'	'PrecCoal'	'$/€'	'Euro Stoxx'
'PrecCO2'	1	0,98304063	0,81349062	0,84891326	-0,31261038	-0,62235438	0,36793911	0,3908417	0,06797757	0,56559792	0,41352927	-0,16063099
'FutCO2'	0,98304063	1	0,82147261	0,86167386	-0,30585152	-0,60968597	0,38562837	0,40383909	0,07918489	0,57257693	0,41997355	-0,14978233
'IndElec'	0,81349062	0,82147261	1	0,92390462	-0,22153882	-0,35627834	0,67446692	0,68629046	0,30447625	0,57466066	0,73217523	-0,02162162
'IndIron'	0,84891326	0,86167386	0,92390462	1	-0,41450282	-0,49900338	0,71758974	0,58950888	0,39614539	0,72287776	0,70481173	-0,24093313
'IndPap'	-0,31261038	-0,30585152	-0,22153882	-0,41450282	1	0,74485512	-0,45358732	-0,21472916	-0,5169954	-0,56390707	-0,51008074	0,87510205
'IndChem'	-0,62235438	-0,60968597	-0,35627834	-0,49900338	0,74485512	1	-0,09770131	-0,10136545	0,01865418	-0,36089923	-0,22034732	0,64116959
'IndOil'	0,36793911	0,38562837	0,67446692	0,71758974	-0,45358732	-0,09770131	1	0,59433746	0,87500923	0,76638819	0,90308774	-0,35247768
'PrecGas'	0,3908417	0,40383909	0,68629046	0,58950888	-0,21472916	-0,10136545	0,59433746	1	0,42156898	0,43678298	0,69099877	-0,0441495
'PrecOil'	0,06797757	0,07918489	0,30447625	0,39614539	-0,5169954	0,01865418	0,87500923	0,42156898	1	0,74550838	0,77800829	-0,53204834
'PrecCoal'	0,56559792	0,57257693	0,57466066	0,72287776	-0,56390707	-0,36089923	0,76638819	0,43678298	0,74550838	1	0,71871808	-0,59525711
'$/€'	0,41352927	0,41997355	0,73217523	0,70481173	-0,51008074	-0,22034732	0,90308774	0,69099877	0,77800829	0,71871808	1	-0,42973516
'Euro Stoxx'	-0,16063099	-0,14978233	-0,02162162	-0,24093313	0,87510205	0,64116959	-0,35247768	-0,0441495	-0,53204834	-0,59525711	-0,42973516	1

"Modelling and forecasting European Union allowance prices applying artificial neural networks"

✓ In the short run:

neural network approach estimated errors

	MAPE	MAE	MSE	RMSE
Naiv	1.6404	0.1003	0.0203	0.1425
1x3x3	1.6557	0.1016	0.0204	0.188
2x3x3	1.2912	0.118	0.0239	0.1542
13x3x1	0.3014	0.1169	0.0253	0.1589
12x3x1	0.233	0.1158	0.0249	0.11578

(K) x (number of previous data used to forecast) x (number of neurons in the hidden layer)

K =
- 1 : Unaltered time series
- K>1 : The time series is broken down into trend and fluctuations. K represents the number of past data used to obtain the trend.

(trend + fluctuations) x (3 previous data used to forecast) x (3 neurons in the hidden layer)

MAPE: Mean Absolute Percentage Error

MAE: Mean Average Error

MSE: Mean Squared Error

RMSE: Root Mean Squared Error

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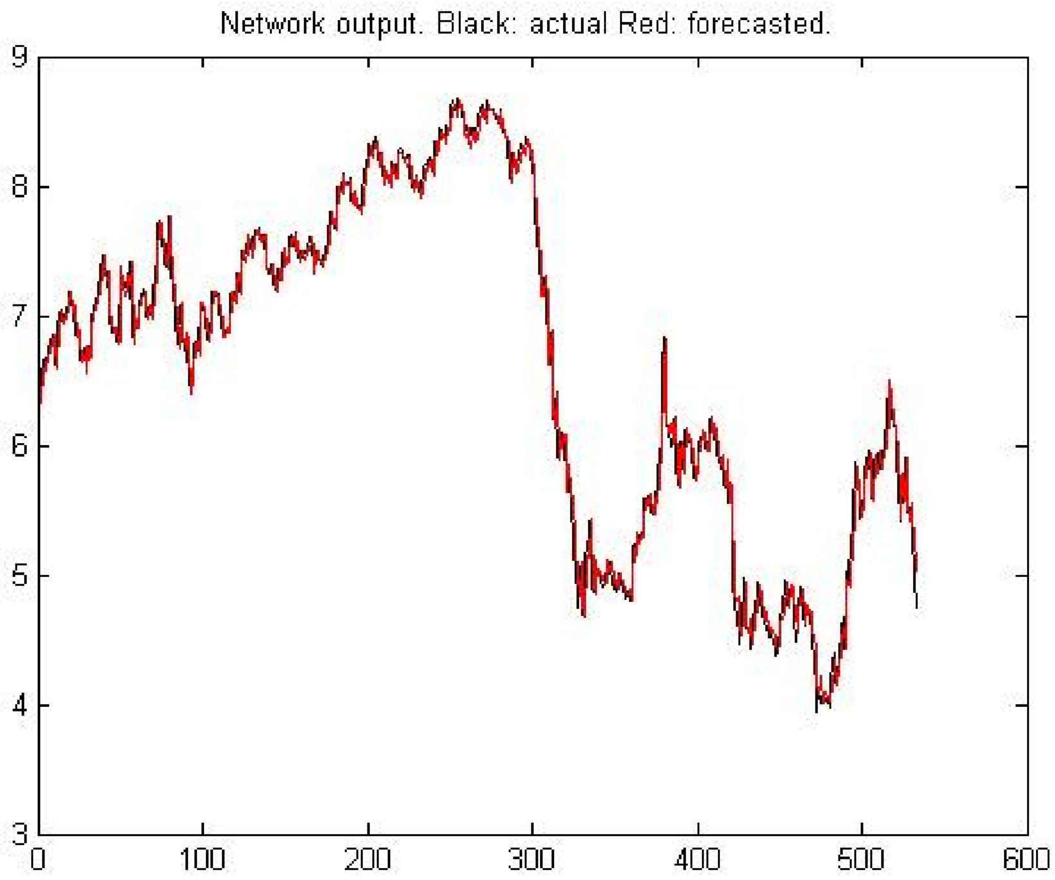
✓ In the short run

neural network approach estimated errors

	MAPE	MAE	MSE	RMSE
2x3x3	1.2912	0.118	0.0239	0.1542



- 1.500 daily data
- Trend and fluctuations
- Low forecasting error
- It doesn’t improve with additional information about pollutant sectors

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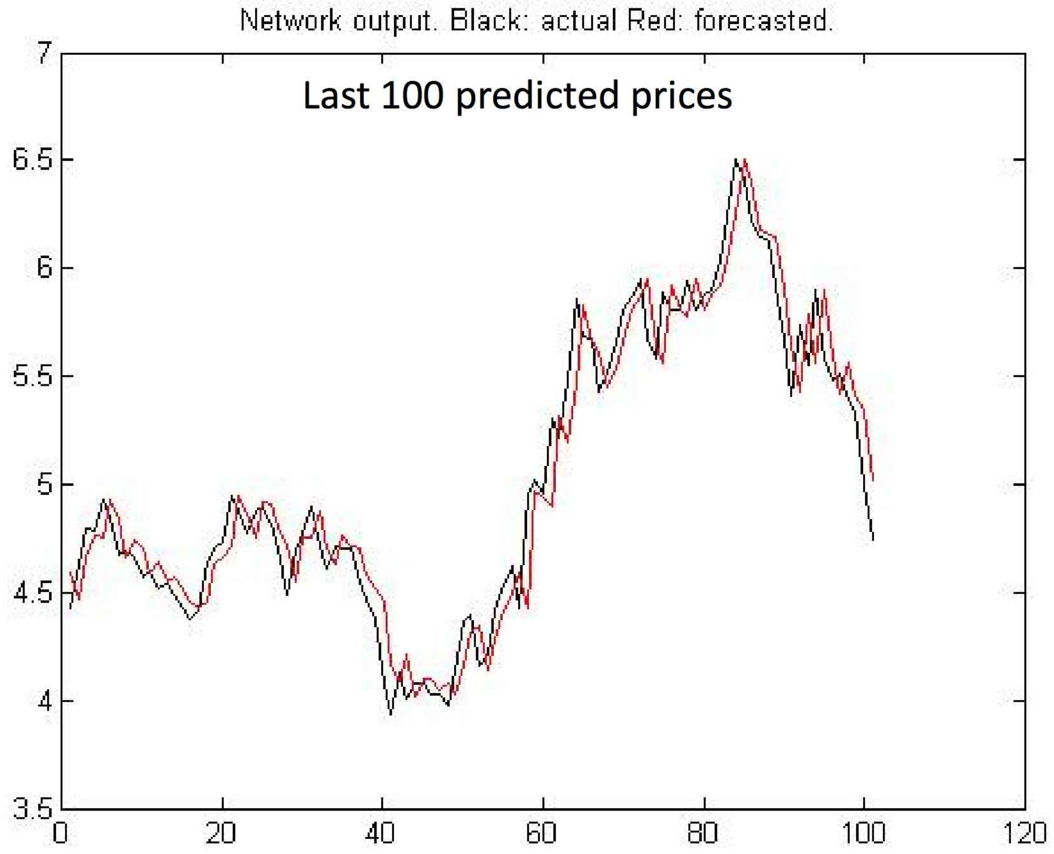
✓ In the short run

neural network approach estimated errors				
	MAPE	MAE	MSE	RMSE
Naiv	1.6404	0.1003	0.0203	0.1425

Naive model: small forecasting error

$$P_{t+1}^{EUA} = P_t^{EUA} + \varepsilon_{t+1}$$



- Optimal temporal distribution
- Profit maximization → Optimal temporal distribution of EUA

$$E_t\left[\pi'(EUA_{t+1})\right] = \pi'(EUA_t) \quad \rightarrow \quad E_t\left[P_{t+1}^{EUA} \middle| I_t\right] = P_t^{EUA}$$

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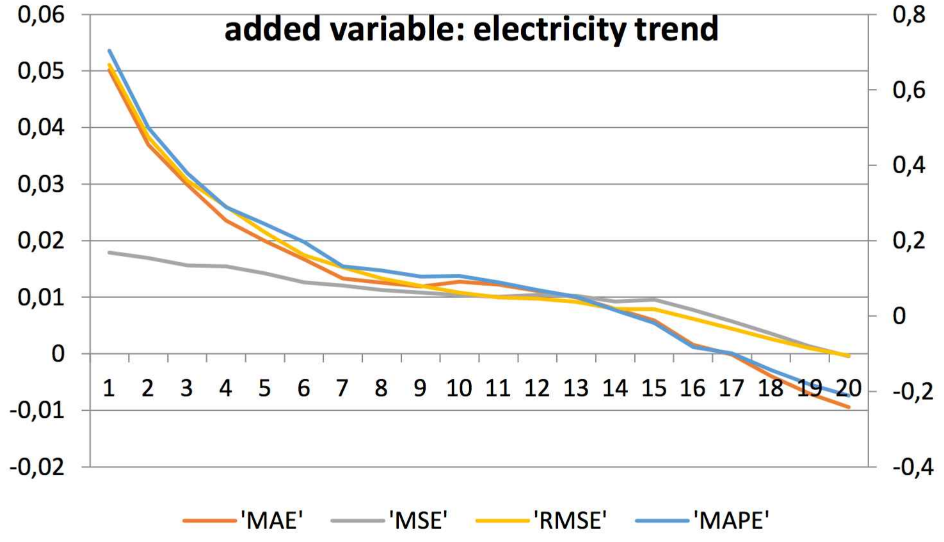
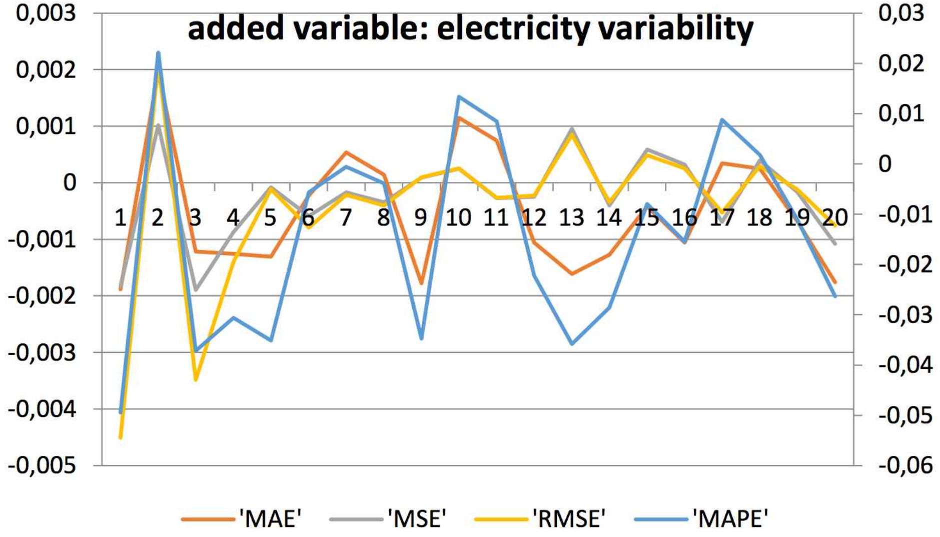
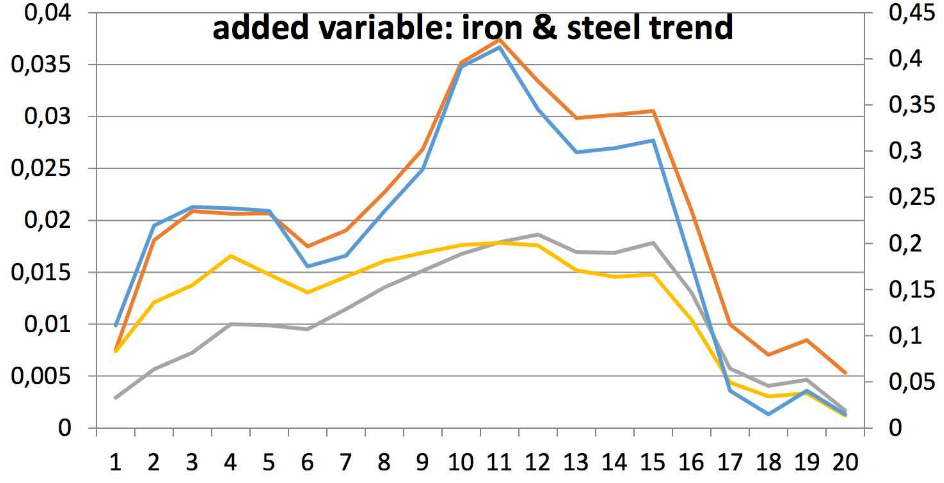
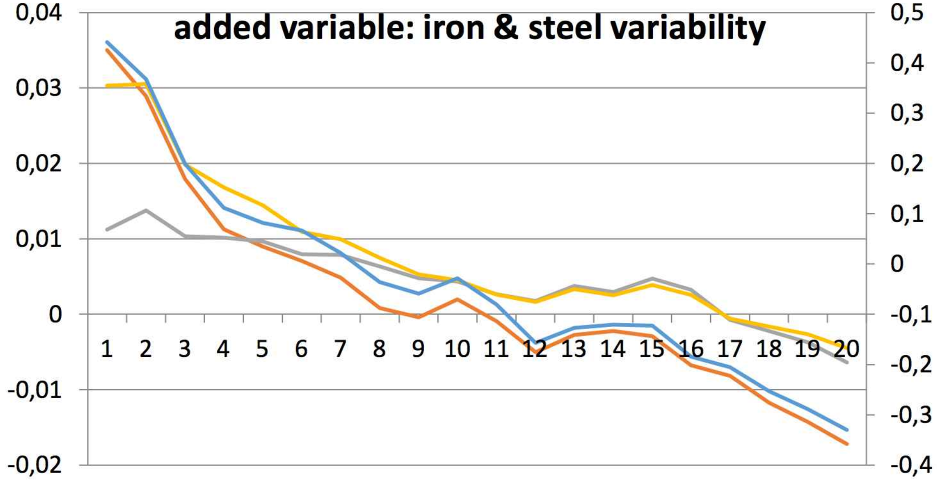
✓ In the long run: pollutant sectors can affect the C02 prices?

Timeframe improvements when additional information is included in the basic neural network model:









"Modelling and forecasting European Union allowance prices applying artificial neural networks"

✓ In the short run:
- EUA similar to financial assets
- only unexpected shocks (policy) can affect the agents (companies) behaviour

✓ In the long run:
- pollutant sectors can affect the C02 prices: power sector and iron and steel industries

"Measuring the impacts of EU allowance prices on the stock market value of the European power industry"

“Measuring the impacts of EU allowance prices on the stock market value of the European power industry”

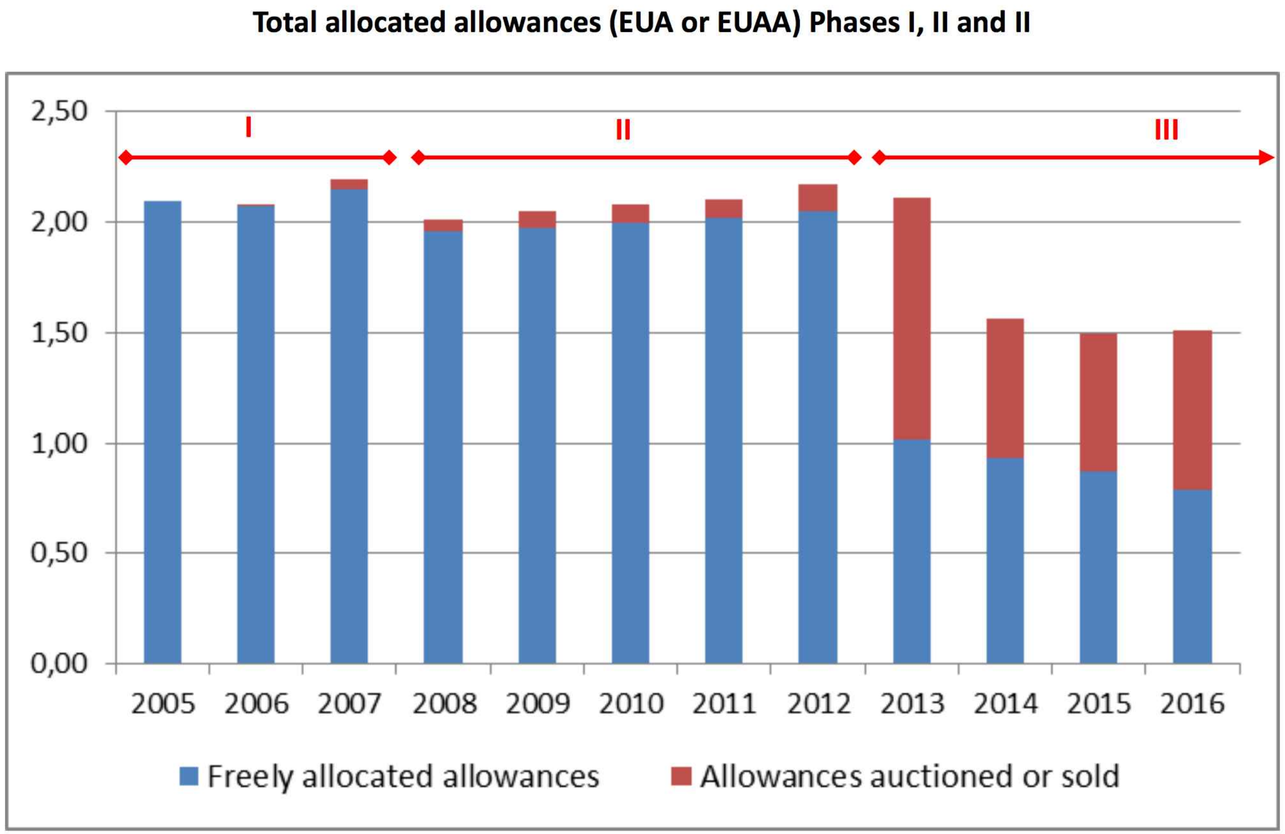
EU Emission Trading System (EU ETS).

- 2005-07: Trial period.
- 2008-12: 90% for free.
- 2013-20: auctioning from 20% up to 70%

asymmetrically distributed

✓ since 2013, the companies in the electricity generation sector no longer receive free allowances

✓ they are supposed to be able to reduce emissions by using new technologies with a relatively low emission abatement cost



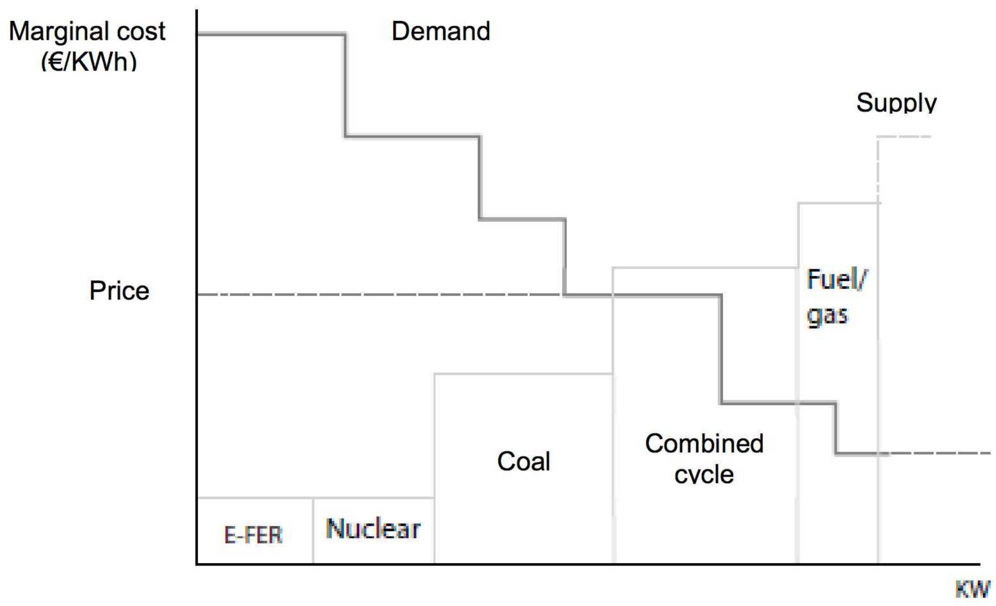
Source: European Environment Agency (EEA)

Final effects on the company profits depend on its capacity to pass on the allowance costs to the consumers and the abatement costs.

Allowance prices could be linked to stock market returns, depending on how the investors evaluate the allowance prices impact on firms’ future profits.

Moreno and Pereira (2016): asymmetric effects (Spain).
Pereira et *al*. (2016): Spanish power sector.

Supply and Demand in the electricity daily market.



Source: García-Álvarez y Moreno (2016)

"Measuring the impacts of EU allowance prices on the stock market value of the European power industry"

We estimate the impact of EUA prices on European power stock market returns:

- cointegration data panel approach
- data from six countries
- daily sample period from 1st January 2013 until 22 April 2017 (more than 3,300 observations)
- 5 common variables (EUA price, fuel prices, currencies) and 3 country-specific variables
- close to 76,000 observations

$$R_{it} = \alpha_{it} + \beta_0 + \beta_1 R_{mt} + \beta_2 P_t^{EUA} + \beta_3 P_t^{oil} + \beta_4 P_t^{gas} + \beta_5 P_t^{coal} + \beta_6 Ir_t + \beta_7 ER_t + \varepsilon_{it}$$

i: Austria, France, Germany, Italy, Netherlands and Spain (α_i: country effects)

Results:

- Allowance prices affect stock firms value
- Fuel prices also affect stock returns

“Measuring the impacts of EU allowance prices on the stock market value of the European power industry”

Results and conclusions:

- EU allowances are similar to a financial assets in the short run
- Pollutant activities (power sector and iron and steel industries) are linked in the large run.
- Allowance prices affect stock firms value (European power industry)
    - The effect is positive and significant (Oberndorfer, 2009 or Pereira et al., 2016)
    - windfall profits, strategic behavior, non-competitive electricity market?
- Fuel prices also affect stock returns
- EU allowance market works properly?
- …

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Thank you

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