# Forecasting the European Carbon Market

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- The scheme caps $CO_2$ emissions, and then distributes allowances to emit to large energy users.

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- But markets should be clear and transparant to achieve these gains

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- DMA gives insight into changing role of various price drivers in the different phases of EU ETS.

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- Forecastability sheds light on maturity and efficiency of such markets

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- Currently, covers 11,000 energy-intensive installations in the power industry and five major industrial sectors (e.g. oil, iron and steel, cement, glass, and pulp and paper)
- Account for nearly half of Europe's total $CO_2$ emissions

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- Other events, e.g. VAT fraud, phishing attacks, recycling of offsets (CERs), which should have been retired

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- Note: in a forecasting exercise cannot have retrospectively chosen dummy variables (even if these were known in advance, their impact on the forecasts would not have been)

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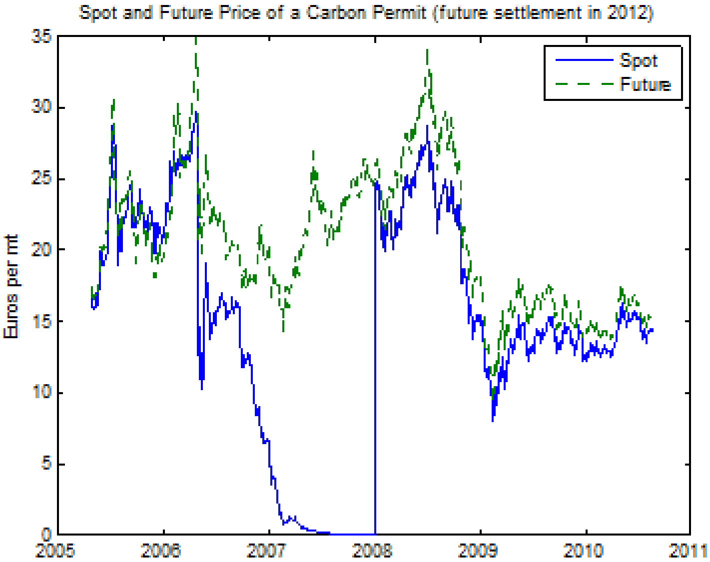
- Main features of data can be seen on figure


Spot and Future Price of a Carbon Permit (future settlement in 2012)
Euros per mt
35
30
25
20
15
10
5
0
2005
2006
2007
2008
2009
2010
2011
Spot
Future

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- We do both (results for combined data as well as each phase separately)

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- DMA, developed in Raftery et al. (2010, Technometrics), satisfies these characteristics

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- If a model has forecast well in recent past, it will get more weight now.

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- TVP model: one single model using $Z_t$
- Constant coefficient models: $\theta_t$ is constant (i.e. a regular regression)

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- MSFE uses only point forecasts (small values indicate good forecast performance)
- Predictive likelihoods are preferred method (use entire predictive density, large values indicate good forecast performance)

| Table 1: Forecasting Carbon Prices | | | | |
|---|---|---|---|---|
| | Spot | | Futures | |
| | MSFE | Pred. Like. | MSFE | Pred. Like |
| DMA | 116.15 | 1707.87 | 0.95 | 2822.81 |
| DMA (no TVP) | 233.73 | 426.84 | 0.94 | 2838.36 |
| TVP (no DMA) | 114.78 | 1664.12 | 1.11 | 2754.59 |
| Const. Coeff. | 250.39 | 358.06 | 1.02 | 2792.73 |

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- Results using Phase 1 and Phase 2 data separately, broadly similar to one another
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- With futures price data forecast performance roughly constant over time

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- Great deal of variation over time in respect ot which price drivers included
- .It is rare for DMA to attach a probability close to one to any particular price driver at any point in time.
- As with previous studies, though, the prices of gas, oil, coal and electricity are often important price drivers.

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- Price of US carbon moderately strong driver over the same period
- Error variance shows a large increase in volatility in two Phases, corresponding to spring 2006,when news broke market of overallocadtion and early 2009, when VAT fraud affected market

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- DMA handles this change well and forecasts well

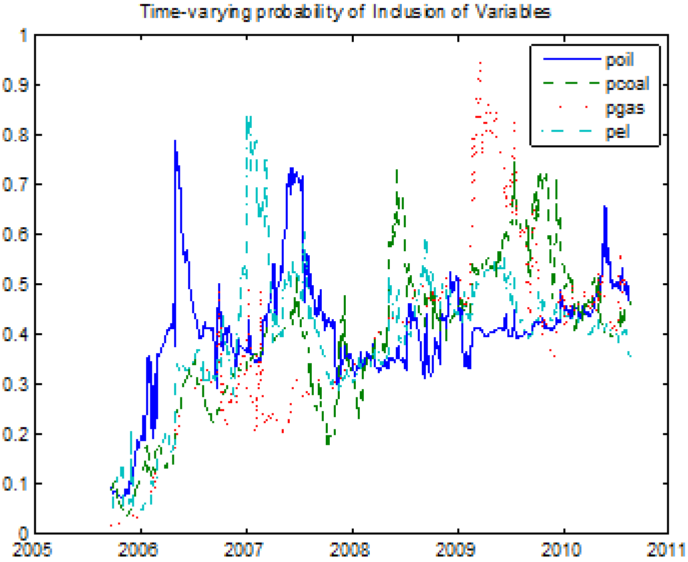


Figure 5: Results for Carbon Futures Price

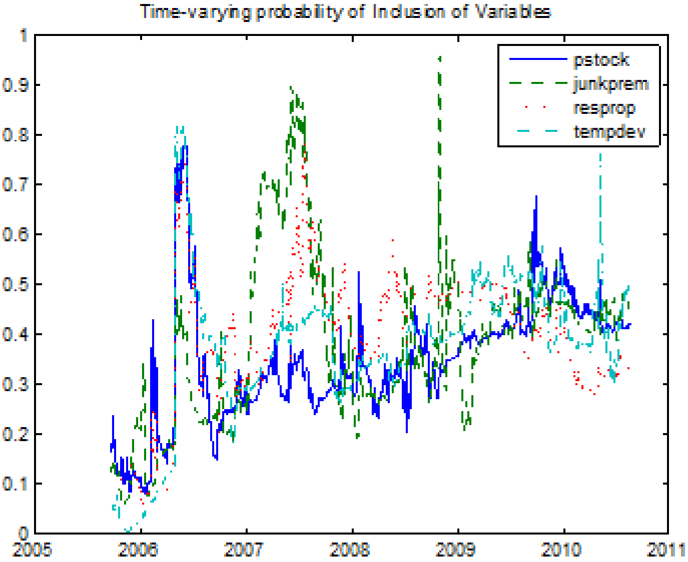


Figure 6: Results for Carbon Futures Price

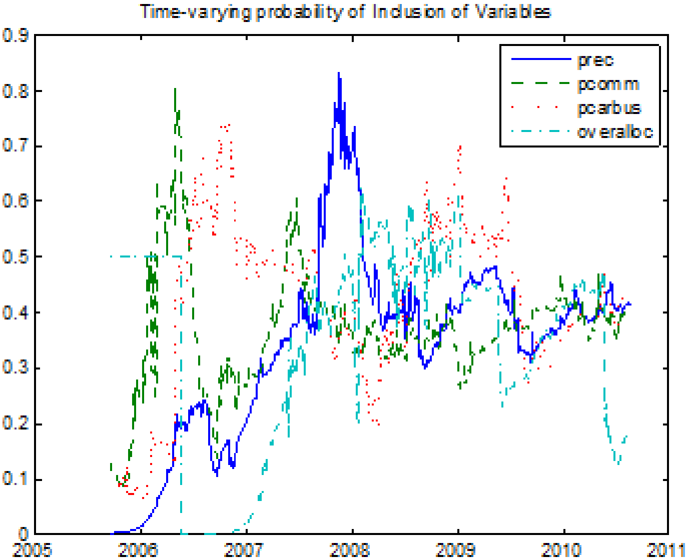


Figure 7: Results for Carbon Futures Price

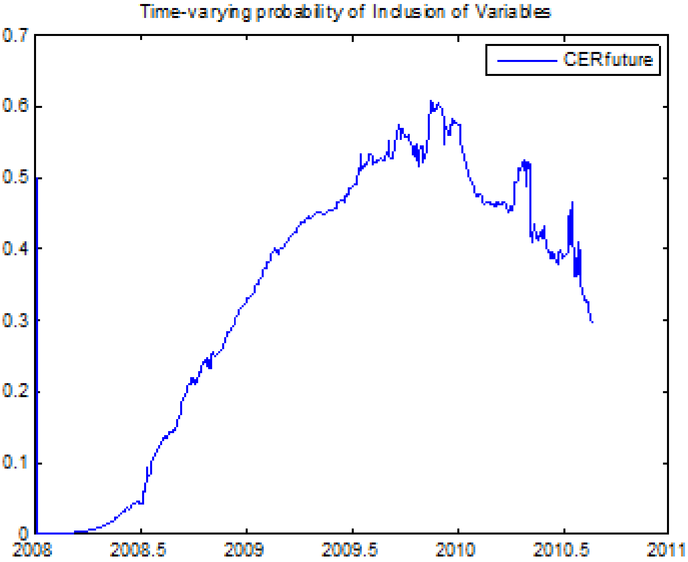


Figure 8: Results for Carbon Futures Price

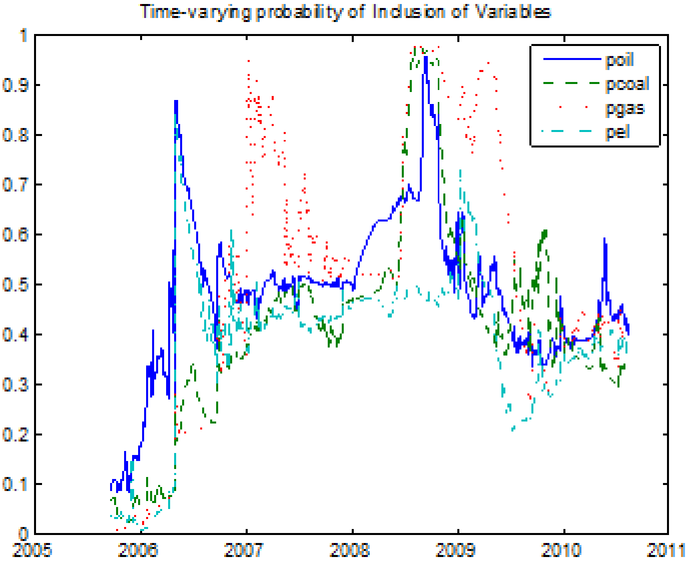


Figure 11: Results for Carbon Spot Price Data

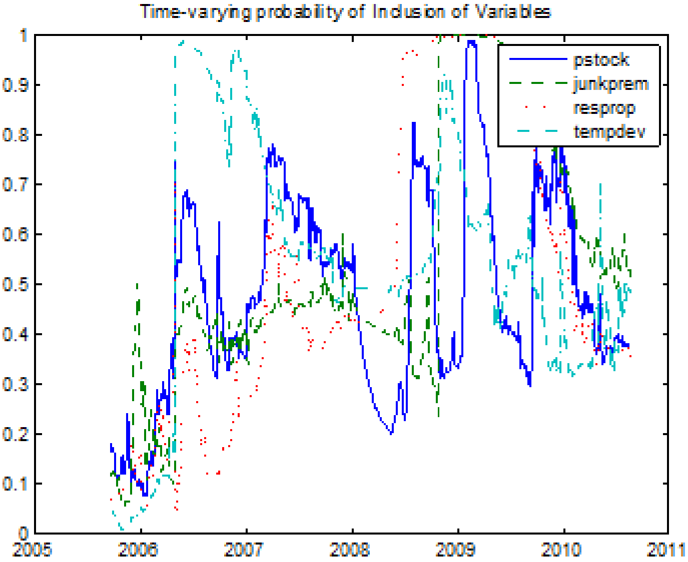


Figure 12: Results for Carbon Spot Price Data

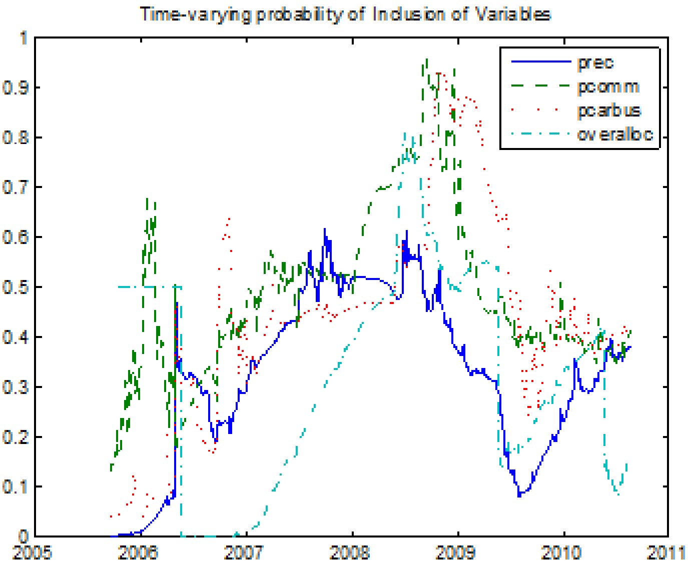


Figure 13: Results for Carbon Spot Price Data