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"Dynamics of CO2 price drivers"

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Dynamics of CO_2 price drivers

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Abstract

Using data from Phase II-III of the European Union Emission Trading Scheme, we characterize CO_2 prices interrelation with energy prices (gas, electricity and coal), carbon allowances substitute prices and with economic activity index. We estimate a vector autoregressive model and the responses of CO_2 prices to impulses in other variables, observing duration and direction of the impact. Our main findings include significant positive impact of returns in CO_2 of peak electricity, gas, and economy index, and CO_2 returns itself. The impact is visible during ten days in case of an electricity innovation, and during one day in case of gas. A shock in economy index prices has 2 days impact, and finally a substitute good for carbon licences in the European market does not have a significant impact.

KEYWORDS: Carbon price; Emission allowances and trading; VAR model

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1 Introduction

The Kyoto Protocol is a contract ratified by several industrialized countries that imposes a limit on their greenhouse gas (GHG) emissions. It also provides three flexibility mechanisms to help countries to reach their goal. Those mechanisms are the Clean Development Mechanism (CDM), Joint Implementation (JI) and Emisions Trading. The first two regard project instruments, where it is possible to obtain emission certificates by developing mitigation projects. The third mechanism, Emissions Trading, distributes emission licenses by countries and allows them to exchange those permits in order to fulfil the predetermined carbon cap. In theory, emission markets allocate reduction efforts where they are least expensive.

The Kyoto Protocol also allows for the implementation of regional emission trading schemes, like the European Union Emission Trading Scheme (EU ETS), operational since 2005. 2005-2008 was called Phase I, a test phase, while Phase II, 2008-2012, was a binding phase for it was at the same time the Kyoto Protocol commitment period, in which European countries had to internationally fulfil Kyoto obligations. 2013-2020 is called post-Kyoto phase and, although some market aspects have changed (essentially new allocation rules, new gases, new activities and new countries), market principals remain the same.

The EU ETS was the first and is the largest GHG emission trading scheme in place, but other regional emission markets now exist within the USA, New Zealand, Japan, Australia, Canada, and at least three are under development (China, Korea, Belarus). Carbon markets are thus a globally recognized solution for the greenhouse gas (GHG) effect problem at the same time providing financial opportunities.

In this reality, carbon prices became subject for large investigation, either to help utilities managers, financial analysts, market regulators or other stakeholders. After almost 9 years of EU ETS it is possible to say that unreasonably low carbon prices, and their causes, are the main concerns for keeping the market operational while actually reducing GHG emissions.

Several authors have studied aspects of carbon prices formation usually using EU

ETS carbon data, most of them after the end of Phase I, the test phase. Granger causality tests have been the most common methodology for interconnection analysis between CO_2 prices and other variables, which usually only considers a one-way influence of variables in CO_2 (Keppler and Mansanet-Bataller 2010; Creti et al. 2012). More recent studies have focussed on volatility analysis and high frequency prices suggesting the use of GARCH models (Aatola et al. 2013; Byun and Cho 2013; García-Martos et al. 2013; Lutz et al. 2013). Others use VAR models to detect and overcome the endogeneity problem and estimate the impact of innovations with respect to other variables (Kumaret al. 2012; Aatola et al. 2013). Kumar el al. (2012) applies this methodology to stock prices of clean energy firms, oil and carbon markets while Aatola et al. (2013) looks at the impacts of changes in electricity prices. Finally, Gorenflo (2013) also relies on a VAR model to study the lead–lag relationship between spot and futures prices of CO2 emission allowances, using data for 2006 and 2007.

Focussing on studies that look at the origins of carbon price changes, relevant studies confirm the impact of the variation of industrial production in EUA price changes (Alberola et al. 2009), and that the relationship between carbon price and the economy is robust to the introduction of energy market shocks (Chevallier 2011). Other results show that in 2008 electricity prices Granger-caused CO_2 prices (Keppler and Mansanet-Bataller 2010), and that gas price has a significant impact on carbon price, and both carbon and gas prices drive electricity prices (Mansanet-Bataller et al. 2007; Fezzi and Bunn 2009). Finally recent studies show a strong relationship between German electricity prices and gas and coal with the carbon price in 2005-2010 (Aatola et al. 2013). Lutz al. (2013) conclude that the most important EUA price drivers are changes on the stock market and energy prices.

Our purpose is to go deeply on carbon price dynamics. Looking at data from 2008-2013, we aim to characterize CO_2 prices interrelation with the most relevant energy, economy, substitute goods and weather variables influencing this market. We specify a dynamic vector auto-regressive (VAR) model, which is usually used to analyse and display interdependencies between different time series. With this model, we can estimate response functions of CO_2 prices to impulses in other variables. These impulse-response functions (IRF) allow us to observe the impact of other variables in CO_2, in terms of duration, direction and magnitude. We also use with data from the Kyoto commitment period, when companies and countries had international obligations to reduce emissions, as they still have now.

Our paper follows a very simple structure. In section 2, we describe the data used in this paper and the econometric VAR theory behind our model. Section 3 reports the empirical results. Section 4 concludes.

2 Data and econometric methodology

2.1 Energy, weather, economy and substitute goods

Controlling for greenhouse gas (GHG) emissions through markets implies that emissions are limited, have a price and may be exchanged. The initially defined overall limit is the fixed emissions allowances supply. Therefore, in this market, the expected price drivers for emission allowances will include main emitters' activity, and variables that affect their production. That is to say energy, economic activity and weather variables.

Taking the above paragraph in consideration and previous work on CO_2 price causality (e.g., Alberola et al. 2009; Fezzi and Bunn 2009; Keppler and Mansanet-Bataller 2010; Sijm et al. 2012; Aatola et al. 2013; Lutz et al. 2013 and Nazifi 2013) our model considers eight variables: CO_2 price, Certified Emission Reduction (CER) price, base and peak electricity price (Elect_b and Elect_p), gas and coal prices (Gas and Coal), average temperature and an European economy stock market index (Econ).

In Figure 1, we can see the energy and emission data variables in levels. One can observe the abrupt decline in all prices between mid-2008 until mid-2009, due essentially to external economy conditions, and after a one year and a half recovery, a slower but constant deterioration in prices. All these variables, as well as their sources, are described in the appendix.[1]

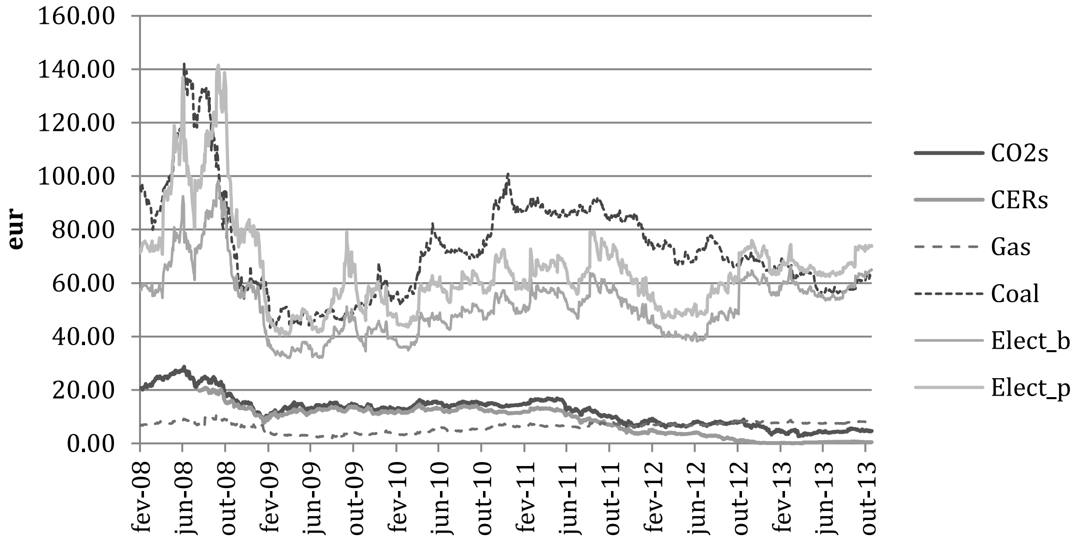

Figure 1 : Prices evolution, 2008/2013

2.2 VAR Model

Vector autoregression (VAR) models capture and show the dynamics amongst several variables considering the influence of their past values. It is an expansion of an autoregression model (AR), where only one variable depends on its past values, but allowing for a vector of several evolving variables. Through a set of impulse-response functions, and after appropriate restrictions identification, it is possible to estimate the dynamic response of a variable to innovations in other variables.

Let Y_t be a vector of stationary variables (in our application, we consider variables in first log differences). The structural VAR model is:

$$BY_t = \Gamma_0 + \Gamma_1(L)Y_{t-1} + \varepsilon_t, \tag{1}$$

where, $\Gamma_1(L)$ is a matrix lag polynomial and Y_t is a vector with the variables gas_t, $coal_t$, ele_p_t, ele_b_t, $econ_t$, $CO2_t$, CER_t. Matrix B reports the contemporaneous

[1] We did not consider variables as the Clean Spark Spread, the Clean Dark Spread or the «carbon switch» (Keppler and Mansanet-Bataller 2010), because they are linear combinations of variables already included.

relations between all eight variables. So the model allows for feedback effect because variables at time 't' may affect each other. The model assumes that ε_{y_t}, called innovations, are white noise. Unfortunately, equation (1) cannot be estimated directly, as OLS would render inconsistent estimates.

Pre-multiplying by B^{-1} the model may be written in a reduced form:

$$Y_t = \mathrm{A}_0 + \mathrm{A}_1(L)Y_{t-1} + e_t. \tag{2}$$

Equation (2) delivers the VAR in its reduced form and can be estimated by OLS. Note that the e_t's have zero mean and constant time independent variances, but their covariances are not zero, meaning that although they are serially uncorrelated, they are correlated across equations. I.e., the shocks in the model are correlated.

The final goal is to estimate how CO_2 responds to impulses in other variables. To derive the impulse response functions, we follow the methodology proposed by Sims (1980) and rely on the Cholesky decomposition to impose short run identification restrictions.

The idea is to impose restrictions in the error covariance matrix of equation 2 in order to recover matrix B of equation 1. These restrictions impose contemporaneous effects of zero in a predetermined direction. By a convenient ordering the variables, we basically impose that the covariance matrix is lower triangular where the first equation does not consider any other innovation rather than its own, the second equation considers the second and the first coming from the addition of the first equation and so on, until the 7th equation that considers them all.

Impulse-Response Function

An impulse, or an impelling force or motion, is what is assumed to trigger the dynamic response of the model. The goal is the analysis of the response, the propagation mechanism, of the variables in the following time periods. The IRF shows the effect of a specific innovation to variable i ($\varepsilon_{i,t}$) on the contemporaneous and future values of all variables.

The process to define these functions starts with the estimated 'composite' e_t residuals (linear combinations of uncorrelated innovations) and from them rebuilds the original innovations ε_t. Following Sims (1980), the process involves representing the VAR model as a Vector Moving Average (VMA) where endogenous variables are defined by e_t shocks. The VMA allows tracking the shocks effects.

To see this, note that Equation (2) may be rewritten as:

$$A(L)Y_t = e_t, \tag{3}$$

Where A(L) is a matrix polynomial in the lag operator L.

Then, considering the VAR model is invertible, it is possible to write it as a Vector Moving Average of infinite order (VMA(∞)):

$$Y_t = A^{-1}(L)\mathrm{e}_t = \omega(\mathrm{L})\mathrm{e}_t. \tag{4}$$

Having the VMA representation, and keeping in mind that $\mathrm{e}_t = B^{-1}\varepsilon_t$, it is possible to estimate the impulse response function. Given a unit change in innovation 'j', or impulse, the system reaction to a shock is given by individual reactions of variables 'i', which are called responses: $\frac{\partial y_{i,t+s}}{\partial \varepsilon_{jt}}$.

As endogenous variables, we have seven endogenous different time series and one exogenous variable. The eight variables are: CO2 spot prices, CER spot prices, peak and base electricity future prices, gas and coal future prices, FTSE300 index and average EU temperatures. With the exception of EU temperatures, all are considered endogenous. Nonstationarity is not a problem, as we considered the first differences of the log variables. This was confirmed but the usual unit root tests. The exogenous variable is also stationary. To choose the number of lags we relied on the likelihood ratio test statistic (which points to 21 lags, corresponding to one month of daily data).

3 Results

3.1 Causality and feed-back relations between variables

A central question in VAR models is the endogeneity or exogeneity of variables, as discussed in the previous chapter. In this study, temperature was the only variable considered exogenous *a priori*. For all other variables, we ran Granger causality/block exogeneity tests to perceive if any variable should be treated as exogenous. In these tests, a χ^2 Wald statistics is given for each equation for the joint significance of each other lagged endogenous variables in the equation, as well as a statistic for joint significance.

The results are described in Figure 2.

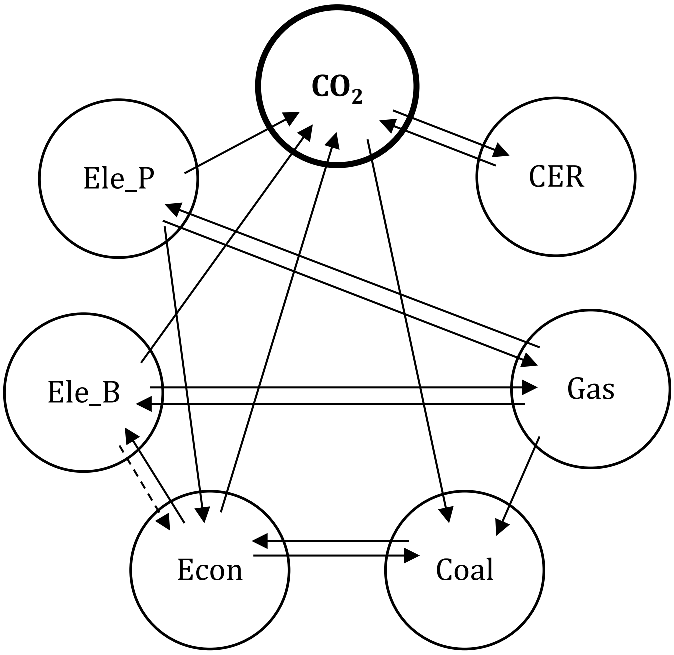

Figure 2: Granger causality/Block Exogeneity Wald Tests, 02/01/2008 - 30-09-2013. Dashed/Continuous Arrows indicate causality at 10%/5% significance.

As we may see in Figure 2, we found interdependences in several variables, and some recurring influence cycles. Recall that the purpose of the Wald test is not to quantify any relation, but instead to identify multiple relations. This analysis allows surpassing the problem of missing variables, present in bivariate causality tests. Additionally, looking at the results of individual and joint significance of lagged endogenous variables, there is no variable that should be considered exogenous in this model.

With the exception of CER, almost all variables are influenced by at least two others. This fact is coherent with the CDM market rationale, where CERs price returns are expected to result essentially from the equilibrium between the supply of CDM projects and demand by countries and emitting installations. Given that the CER demand is somewhat minor[2], prices in this market are mostly ruled by the supply of mitigation projects. Some of these variables are reflected in this model, as inputs to CERs: CO_2, for CERs are EUAs substitutes; peak and base electricity for large part of CDM projects regard renewable electricity generation or fuel switching projects; and the economy, because of the incentive to industries to invest in CDM projects.

Regarding **CO_2**, its returns are significantly caused by the economy returns, peak/base electricity price returns and CERs prices. Although most authors consider a direct influence of gas and coal prices in CO_2 prices (e.g., Mansanet-Bataller et al. 2007; Fezzi and Bunn 2009), in our model those influences are captured through the electricity price. It is also worthwhile to note some indirect channels. For example, Gas influences both peak and base Electricity, which in turn influences Economic Activity, which causes **CO_2**. Therefore, even if we do not find a direct influence running from gas and coal prices to **CO_2** prices, we do find indirect linkages.

In the case of **peak electricity**, gas price has significant explanatory power, a result in line with the findings of Fezzi and Bunn (2009). This is an adequate result given that natural gas is an important primary energy for thermal electricity production. Natural gas has a lower GHG emission intensity (469gCO_2/kWhe[3]), and more flexible supply, when comparing to coal. In this model **gas** and peak (and base) electricity returns have a feedback effect meaning that previous values of each one influence both contemporaneous values. This is also an acceptable result given that utilities define their generation mix looking at past values of electricity

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[2] During the period considered only the European carbon market recognizes CERs as substitutes for EUAs, and only up to a small percentage (globally an average of 10% per emitting installation).
[3] Moomaw, W. et al, 2011, "Annex II: Methodology. In IPCC: Special Report on Renewable Energy Sources and Climate Change Mitigation" (ref. page 10), http://srren.ipcc-wg3.de/report/IPCC_SRREN_Annex_II.pdf , retrieved 18/03/2013

and primary energy prices.

Regarding energy variables we only found evidence for a significant influence of CO_2 in coal returns in 2008-2013. This result somewhat bias the carbon market principle of CO_2 influencing overall electricity prices, but follows the current general opinion that carbon prices are too low to have an impact.

Finally, the economy, gas and CO_2 price returns influence **coal** price returns. This last result could benefit from further study, given the very high emission intensity levels (1001gCO_2/kWhe[3]) of electricity generation with coal. However it is an aspect that falls out of this study main purpose, and so we leave it for further developments.

3.2 Impulse Response Functions

As discussed earlier, it is necessary to choose a Cholesky ordering of the variables. We considered gas being influenced only by its own innovation, then coal to have its own and be influenced by the gas innovation, then peak electricity, following the same reasoning having its own innovation, and the ones from coal and gas, after, base electricity, then the economy, CO_2, and finally CERs. This choice reflects carbon market price principles by which it captures influences of industrial output levels, effects of mitigation actions, and economic circumstances. Also, it follows suggestions in block exogeneity Wald tests presented above. In the end, this particular ordering is not important as_our results revealed to be robust to different orderings.

There are 49 (7 × 7 variables) IRF in this model. It would be purposeless to show them all. Recalling the goal of this study to analyse CO_2 responses to shocks in other variables, we will look to the seven IRF that show this. For IRF display we selected the accumulated responses because variables are in first log differences, so the interpretation should be clearer. We also tested for several response periods and 10 days proved to be enough to show the accumulate response asymptote to a non-zero constant.

Figure 3 : Accumulated response of CO2 to impulses in:

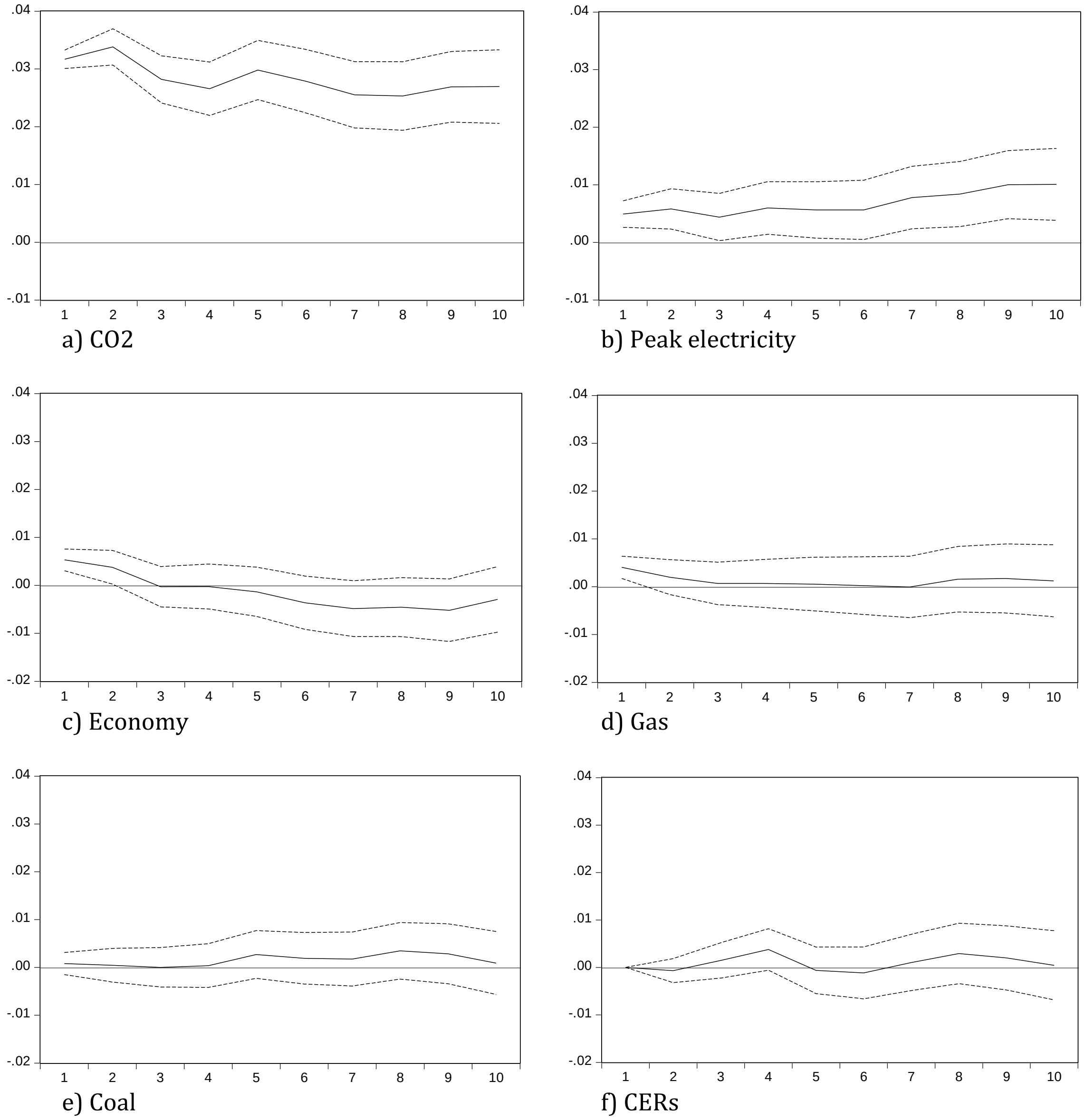

Figure 3 represents the accumulated response of CO_2 to one standard deviation innovation of gas, coal, peak electricity, economy, CO_2 and CER, +/- 2 standard errors.

In Figure 3.a, we see that the impact of CO_2 innovations on itself is always positive and significant. After two days this impact almost stabilizes, and then, although still positive, it slows down in the 6th to the 7th day, only to start rising again and stabilizing. Because these are accumulated responses, it is possible to see that an impulse from CO_2 will positively change CO_2 returns and that this change will endure, which was an expected result.

In Figure 3.b we may see the response of CO_2 price returns to an innovation in peak electricity price returns. The impact is significant in all periods and increasingly positive. Globally this is also an expected result, for electricity generation emits a large part of the CO_2 considered in the market. So, if there is a positive change in peak electricity prices variation, it is expected that CO_2 prices variation will act accordingly. There is a visible response in the following 10 days, and in the end the change in CO_2 price levels will sustain.

Regarding the role of the economy, in 3.c, the contemporaneous and the 2nd day impact in CO_2 returns is positive. That is saying that economy and emissions move in the same direction. This is the third expected result of this study: as CO_2 emissions origin is mostly energy intensive production, and this production is known to be highly related with economy levels, it is expected that a positive change in the economy returns has a positive response from CO_2 returns. The novelty is that this impact is transitory, given that it is significant only in the first two days.

Looking at natural gas,we see a marginally significant positive impact in CO_2 returns in the first period. After the second day the results are not significant. This result from the natural gas shock is in line the findings of Fezzi and Bunn (2009), andconsistent with the definitions of Clean Dark and Spark Spreads that analysts and utilities consider in their decisions for the generation mix. As referred in the data description chapter, these spreads are linear combinations of electricity, carbon, coal and gas prices, displaying the most cost-efficient option for electricity generation in one period, either using coal or gas power plants. What we show in this result is that changes in the natural gas prices are immediately considered in the carbon price variation.

Finally, in Figure 3.f, changes in certified emission reductions prices, or CER, associated with clean development mitigation projects in developing and least developed countries, have no immediate impact in CO_2 price changes. It is an important result that CER price changes had no expected impact in the European carbon market during 2008-2013[4], confirming previous results regarding EUA-CER

[4] However, the CDM market is undergoing a phase with over-registration of projects, which caused

spread (Mansanet-Bataller et al. 2011).

A final result is that significant impacts from CO_2 and peak electricity price returns don't fade overtime. This means that whatever impact in CO_2 a shock from these variables has, it will withstand in future periods.

4 Concluding remarks

In this paper we aimed at characterizing the relation between CO_2 prices and energy prices, certified emission reduction prices and economy index prices. We estimated a VAR model considering all variables endogenous. We included temperatures as the only exogenous variable. Daily data from Phase II and one year of Phase III (2008-2013) of the EU ETS was used.[5]

Regarding CO_2 price returns, we found significant effects from electricity price returns and the economy index. This supports the idea that main power utilities could have influenced CO_2 price in 2008-2013. No evidence was found of CO_2 influence in energy variables. This result has important implications for it suggests that the initial purpose of pricing carbon is not having the intended result of influencing energy prices, or at least, electricity prices. This outcome follows the current general opinion that carbon prices are too low to have an impact.

When we consider a positive impulse in variables our results suggest a positive response of CO_2 returns in all cases except for CER and coal. Looking at the other variables, an impulse of electricity price had a 10 days impact in CO_2 returns, and of gas a 1 day impact. The economy had 2 days impact. Finally, CO_2 returns also had a 10 days impact in itself.

It is important to note that this study was conducted using data from 2008 to 2013, in Europe, meaning that the current economic and financial crisis has possibly in-

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CER prices to start falling since the beginning of 2012. In 2013 they reached the lowest levels ever recorded. Knowing this, emitters started to buy swaps CER-EUA derivatives for they have an immediate profit margin in buying CERs and selling EUAs. This event may be reflected in the next few years in the EUA carbon price, and then a change in the presented IRF function may be expected.

[5] Restricting our analysis to 2008-2012 would yield similar results. These results are available at request.

fluenced our results. It will be interesting to complete this analysis with analysis from other carbon markets, namely with different operation and accounting methodologies and economic conditions. Also, in a better economic context, a more detailed analysis of responses of energy variables to impulses in CO_2 should be motivating for energy analysts.

Finally, our results suggest that it is crucial to find policies that will allow for CO_2 prices to influence energy prices, in order to incite emissions reductions.

Appendix: data description and sources

CO_2

The European Union Emissions Trading System (EU ETS) is the first and the largest international system for trading greenhouse gas emission allowances. 2008-2013 is the time length of this study representing EU ETS Phase II (2008/2012) and one year of Phase III (2013-2020). Considering this, as CO_2 variable we used the European Union Allowance (EUA) spot price, the unit of the EU ETS, referring to the emission of one tonne of CO_2 equivalent. EUA future prices were not included because of spot-future high correlation level (99%).

Data for CO_2 was available from 2008/02/26 up to 2012/11/01, from Bluenext[6], the most important EUA spot market in volumes then. From Nov-2012 until 12/11/2013 prices were collected from SendeCO2[7]. There is data missing from around 40 days, which did not prove to be of any concern, given the almost 5 years of daily data available.

Certified Emission Reductions (CERs)

Installations covered by the EU ETS have the possibility to accomplish their emission targets surrendering Certified Emission Reductions (CERs), in addition to EUAs. A CER is an emission unit concerning reductions within the Clean Development Mechanism (CDM), a market-mechanism under the Kyoto Protocol. Within this mechanism, emission reductions are issued from mitigation projects in least developed, and developing countries that ratified the Protocol. The market supply of CERs is controlled by the Executive Board to the CDM that evaluates those projects. CERs are then traded in secondary markets.

Although there is currently a political debate on the role of CERs because of a continuous price fall since 2012, Phase II market rules accepted CERs as partial substi-

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[6] Although Bluenext closed permanently its spot and derivatives trading operations as from December 5, 2012, the environmental trading exchange has hosted the largest amount of spot trades, totalling 29.4 million tons [in 2012]. In http://www.bloomberg.com/news/2012-10-26/bluenext-carbon-exchange-to-shut-after-losing-eu-auction-bid-1-.html , retrieved 11/03/2012.

[7] www.sendeco2.com , Iberian carbon emission stock exchange, retrieved 15/11/2013.

tutes for EUAs. This rule has been maintained in post-Kyoto phase. . The price spread between EUAs and CERs was of great importance at least until 2012 (Nazifi 2013). For this reason we considered its spot daily price in this study. Data was gathered from Bluenext for after 12/8/2008. From Nov-2012 until 12/11/2013 prices were collected from SendeCO2. Minor missing data proved not to be a problem.

Energy

Greenhouse gas emissions considered in the European carbon market come from fossil fuels burning and follow a top-down accounting methodology. In the end, more than 11000 power stations, industrial plants and airlines, in Europe, operate under GHG emission limits. Hence, energy markets have an expected importance in the variations of CO_2 price, and, because of this, energy prices were considered in our model. We included typical prices for natural gas, coal and electricity in Europe as energy variables. For all, one month future contract was selected. This choice is in line with the established notion that in energy future prices lead spot prices essentially due to the difficulty of storage, and consequent ease of shorting.

Regarding natural gas prices we used The Intercontinental Exchange Futures[8] (The ICE) data. Originally in £/therm, the data was transformed to Euros/MMBTU for compatibility with other variables and better perception[9]. As for coal one month future prices, they were also retrieved from The ICE database. Coal prices are cost, insurance and freight (CIF) with delivery in Amsterdam, Rotterdam and Antwerp (ARA). They were originally in USD/tcoal and were converted to EUR/tcoal. For electricity, the Phelix baseload and peak prices[10] were retrieved from the European Energy Exchange (EEX)[11], in Euros/MWh. Baseload and peak prices reflect different electricity generation mixes and thus are relevant in our analysis. The Phelix prices regard the German/Austrian market area. They were selected as representatives of the European base and peak electricity prices since Germany is the largest

[8] We thank The ICE from providing us the data for natural gas and coal used in this paper.
[9] Historical exchange rates available at the European Central Bank website: www.ecb.int.
[10] Because electricity needs are not constant all through the day, and it is a non-storable good, we considered two typical electricity prices: peak, that represent prices for a time of day when supply is significantly higher than average levels, and base, an average for the rest of the day.
[11] We thank EEX for providing the data on electricity prices used in this paper.

electricity producer in Europe, which combined with Austria reached 680TWh[12] of generated electricity in 2011. Also correlation levels between Phelix data and other electricity prices (tested for France and UK) range from 0,87 to 0,95. So, variations presented through Phelix prices should appropriately represent variations in other European electricity prices. Finally, there are almost no gaps in energy prices (only 14 days missing data).

Weather

Average daily European temperatures were considered in this study. They were calculated based on the average daily temperatures from regions of 7 representative EU countries (Austria, Germany, France, Italy, Netherlands, Spain and United Kingdom), retrieved from the European Climate Assessment & Dataset[13]. It is a weighted average considering the population of each region[14]. The result is an European average daily temperature index, which was included in the model as the only *a priori* exogenous variable. Data is available until 30/09/2013. For consideration of global warming effects, temperature would have to be endogenous. However, this aspect would only be relevant if we had data for several decades, which is not the case.

Economic activity

Noting that industries included in the EU ETS are energy intensive, and thus their production levels are highly associated with general economic growth, we considered necessary the inclusion of a variable which mirrored economic activity. This is in line with several previous authors in the subject (Alberola and Chevallier 2009; Chevallier 2009; Keppler and Mansanet-Bataller 2010). For this purpose we considered the FTS Eurofirst 300 Index (E3X.L), available at YahooFinance. It is a capitalization-weighted price tradable index measuring the performance of Europe's largest 300 companies. Daily price returns were included, and there is no missing data in this variable.

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[12] BP Statistical Review of World Energy 2012 www.bp.com/statisticalreview
[13] eca.knmi.nl
[14] Following the methodology used by Tendances Carbone for the European Temperature Index www.cdcclimat.com/-Tendances-Carbone-.html

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