DISCUSSION PAPER

August 2008 ■ RFF DP 08-31

EU-ETS and Nordic Electricity

A CVAR Analysis

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RESOURCES
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EU-ETS and Nordic Electricity: A CVAR Approach

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Abstract

A cointegrated vector autoregressive (CVAR) model is estimated to determine the dynamic relationship between Nordic wholesale electricity prices and EU emissions trading scheme (EU-ETS) CO_2 allowance prices. An impulse response analysis reveals that electricity prices have large short-term responses to CO_2 price shocks, but that this response dampens over time. Using hourly Nordic electricity spot market prices, I find that the value of short-term response of electricity prices to a shock in CO_2 prices in off-peak hours is consistent with expected values for near complete pass-through of CO_2 emission costs when coal-generated power is at the margin. Likewise, the estimates reveal that peak hour electricity price responses to CO_2 price shocks are as expected for a market that has near complete pass-through of CO_2 emission costs when natural gas-generated power is at the margin. These results further suggest the Nordic electricity market is pricing as a competitive market.

Key Words: cointegrated vector autoregression, impulse response, electricity markets, CO_2 cost pass-through, EU-ETS

JEL Classification Numbers: Q40, Q48, Q52, C32

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Harrison Fell*

1. Introduction

In order to reach the emissions reduction goals set forth in the Kyoto Protocol, the European Union implemented a memberwide CO_2 emissions trading scheme (EU-ETS). Under the EU-ETS, some 11,500 CO_2-emitting installations from the energy production industries, metal industries, mineral industries, and pulp and paper industries must obtain a sufficient number of emissions allowances (EUAs) to cover their individual annual CO_2 emissions (Ellerman and Buchner 2007). Electricity generators dominated this primarily free initial allocation of allowances, garnering roughly 60 percent of the EUAs in Phase 1 and Phase 2 of the EU-ETS. The free allocation to electricity was nearly sufficient to cover all electricity generation.

The impact that these freely given allowances have had on electricity prices has been a source of controversy and curiosity in political and academic circles alike. From an economic theory perspective, the use of allowances to cover emissions places an opportunity cost on the installation in question regardless of how the allowance was allocated since that allowance could have been sold. Thus one would expect electricity generators to add the cost of emissions to other production costs (Burtraw et al. 2002). While generators may fully recognize the opportunity costs of CO_2 allowances in their marginal production costs, these costs might not be fully passed through to wholesale electricity prices. Sijm et al. (2005) give a host of reasons why the pass-through of CO_2 costs for the firm and for the industry may be less than 100 percent, including among other reasons demand responses, market structure, and competition from nonfossil fuel generators. Thus, determining the response of electricity prices to CO_2 emissions costs for a given market appears to require an empirical approach.

From a policy prospective, some governments are clearly not comfortable with the notion that these opportunity costs should be fully reflected in electricity prices. This was evident when in December 2006 the Bundeskartellamt (German Federal Cartel Office) issued a warning to German electricity generator RWE, claiming RWE was abusing its market position by

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excessively passing through CO_2 emissions costs.[1] In addition, many have noted that the pass-through of these opportunity costs could be generating "windfall profits" for electricity generators stemming from a change in revenues that exceeds the change in costs. These claims of windfall profits have prompted many policy makers as well as academics to call for a greater percentage of electricity generators' allowances to be auctioned instead of freely allocated. Knowing the percentage of allowances that should be auctioned again requires an empirical understanding about the relationship between CO_2 emissions costs and electricity prices.

In this paper, I empirically look at the dynamic interaction of the EU-ETS prices and wholesale electricity prices for a particular European market, the Nordic region electricity market of Denmark, Finland, Norway, and Sweden. The Nordic electricity market presents an interesting application for several reasons. First, the Nordic electricity market is a large, well-established, and transparent deregulated market. Given that deregulation of electricity markets is beginning to spread across Europe and elsewhere, understanding how CO_2 emission prices affect the Nordic electricity market can give insight in to how the liberalization of electricity markets will interact with market-based environmental programs in other situations. Second, the Nordic electricity market has a wide range of electricity-generating technology, including a substantial portion of nonfossil fuel generation capacity. This gives some insight into how the response of electricity prices to CO_2 emissions costs is affected by the electricity production mix.

The influence of carbon pricing on electricity markets has been examined in several other studies. The bulk of this work has been conducted by using large-scale simulation models (e.g., Burtraw and Palmer 2008, Chen et al. 2008; Kara et al. 2008; Linares et al. 2006; Burtraw et al. 2005; Hauch 2003). With an expanding data set available on EUA prices, empirical studies in this area are also becoming more prevalent, although relatively few exist. Sijm et al. (2006) used electricity pricing and generation data from Germany and the Netherlands to estimate CO_2 cost pass-through. They found that, depending on the fuel used by the marginal generators, pass-through varied between 60 and 100 percent of CO_2 costs. Zachman and von Hirschhausen (2007) also used data from Germany to find evidence of asymmetric CO_2 cost pass-through. In a study methodologically similar to the one presented here, Bunn and Fezzi (2007) estimated the relationship among electricity, natural gas, and EUA prices in the United Kingdom, finding a long-run marginal response of electricity prices to EUA prices of 0.42.

[1] Ironically, economic theory predicts that monopolist and oligopolist generators would actually pass through less of the CO_2 emissions costs than those in competitive markets. See Sijm et al. (2005, 33) for details of this argument.

Estimating this interaction presents several challenges. First, even given full pass-through of CO_2 costs, the level of the electricity response to changes in CO_2 may not be constant across time. The CO_2 emissions associated with electricity generation will be a function of the generation fuel used. This in turn makes the increase in marginal cost of electricity generation due to the creation of a CO_2 market dependent upon the fuel type used in generation. Since competitive electricity pricing is based on the cost of the marginal generator, the increase in electricity prices due to CO_2 emissions prices will depend on the generation technology of the marginal producer. If the electricity market in question has generation technologies at the margin that vary over time, such as in the Nordic electricity market, then the electricity price response to CO_2 price changes will be variable. For instance, if at peak electricity demand the marginal producer is a natural gas-fired turbine while at off-peak hours the marginal producer is a coal powered station, then because coal has greater CO_2 emissions intensity than natural gas, it would be expected that the response of electricity prices to CO_2 allowance prices during the off-peak demand periods would be greater than during the peak periods. This complicates the estimation of the electricity price responsiveness to CO_2 price changes because electricity generation profiles are not explicitly observed in most data sets, including the data used here.

In addition to the possibility of varying responses, one must also consider multiple market interactions. That is, changing prices in one market may directly impact pricing in several markets, and these impacts can then have further feedback effects into the system of prices. For example, say an increase in EUA prices leads to an increase in electricity prices and a concurrent increase in natural gas prices because of the increased demand for natural gas-fired electricity generation, which gains an economic advantage over coal-fired generation through the change in relative production costs. The increased natural gas prices may then lead to a further increase in electricity prices, assuming natural gas–fired turbines are at least occasionally price-setting marginal generators. Further, the change in relative production costs may change the option value of using storable non-emitting generation including hydroelectricity, which is an important part of the Nordic power supply. These relationships call for an estimation procedure that accounts for interdependencies of the entire system of prices as well as being able to account for time-specific marginal impacts.

In order to address this latter problem, I estimate the relationship among Nordic electricity prices, EUA prices, and the prices of various generation fuels through a cointegrated vector autoregressive (CVAR) model. The response of electricity prices to CO_2 price changes is then assessed in an impulse response analysis. This allows us to see how a shock to the EUA market propagates through the electricity market in a way that accounts for the interrelated system dynamics. To address the former problem of different fuels being at the margin, we generate electricity price series that are sampled from different hours of the day and different price levels within a day in an attempt to get price series that are indicative of various electricity generation profiles. This procedure allows us to see at least superficially if there is evidence of any variation in electricity price response to CO_2 price increases.

The rest of the paper is organized as follows. In the next two sections, I present background information on the Nordic electricity market and details of the estimation technique. Estimation results and discussion of these results follows. In the final section, concluding remarks are given.

2. Nordic Electricity Market Background

Beginning in the 1990s, the Nordic-region countries of Denmark, Finland, Norway, and Sweden began to deregulate their wholesale electricity markets. As the markets liberalized they also integrated. In 1996 Norway and Sweden started Nord Pool, the world's first multinational power exchange. Finland joined Nord Pool in 1998 and Denmark followed in 1999. In 2002, the spot market operations were organized as a separate company, Nord Pool Spot. As of 2006, the Nord Pool Spot market had more than 300 participants and an annual trading volume of 249.8 TWh (http://www.nordpoolspot.com/about/).

The Nord Pool Spot market, Elspot, is the market for trading physical day-ahead contracts. The price is formed as follows. In the morning prior to the day of physical delivery, electricity generators (consumers) submit capacity bids (asks) for each hour of the day to the market coordinator.[2] The "system" price is then set at the intersection of the bid and ask curves. Transmission capacity permitting, this system price is the hourly day-ahead spot price.[3] Transmission capacity problems are resolved by forming region-specific prices based off the system price.

As one may expect given the relatively large and diverse geographical area represented in the Nord Pool market, electricity generation varies considerably across the regions. Table 1

[2] Bids can be submitted for time blocks other than just hourly. However, hourly bids are the finest time blocks, and data from the hourly day-ahead market are the focus of this study.

[3] The wholesale electricity market among the four countries is near fully liberalized, but transmission remains as government-regulated monopolies.

shows the electricity generation profiles of the Nordic countries based on 2005 production. As Table 1 shows, electricity generation in Norway and Sweden, which rely almost exclusively on hydro and nuclear energy, is essentially CO_2-emissions free. However, both Denmark and Finland have considerable coal and natural gas generation. Generators using these fuels will then have a need for EUAs. Thus, when these generators are the marginal producers it is expected that the EUA price, along with the price of the fuels, will influence the Elspot price.

3. Data and Empirical Methodology

In understanding the interaction of EUA prices and Nordic electricity prices, there are many intricate relationships to consider. For instance, given the electricity production profiles of Denmark and Finland, it would appear likely that coal and natural gas prices will influence electricity prices. Mansanet-Bataller et al. (2007) and Alberola et al. (2008) also find that among other variables, EUA prices are influenced by coal and natural gas prices. Reservoir water level has also been shown to affect Nordic electricity prices given the region's use of hydroelectricity (Koopman et al. 2007). Conversely, if hydroelectricity is generated strategically, reservoir levels will also be a function of electricity prices. Given these various relationships, a systems-based approach is used here.

This study uses weekly data running from the week ending on January 7, 2005, to April 18, 2008. EUA price series (P_t^{EUA}, €/ton emitted) is the weekly average of spot price as quoted by Point Carbon. The natural gas price (P_t^{g}, €/Btu) is the weekly average of spot prices from the Zeebrugge hub. The coal price (P_t^{c}, €/ton) used is the weekly average of spot prices for coal delivered to the Amsterdam/Rotterdam/Antwerp region. Electricity prices (P_t^{elec}, €/MWh) come from the hourly day-ahead Elspot system prices for weekdays only.[4] Several different averaging mechanisms are used to derive price series and will be discussed in more detail below. However, for the base case, the electricity price used is the average of all weekday hourly prices. To control for reservoir levels, a measure of water scarcity is needed. The series used for this measure is

$$(level)_t = (percent\ of\ capacity)_t - (\overline{percent\ of\ capacity})_t$$

[4] Weekend electricity price data are excluded from this study because demand patterns, and thus price patterns, are substantially different from weekdays.

where $(percent\ of\ capacity)_t$ is the percent of the Nordic region's reservoir capacity that is filled for week t and $(\overline{percent\ of\ capacity})_t$ is the historical average of percent of capacity for week t (source: Swedish Environmental Research Institute IVL). Air temperature is also often cited as an important determinant of electricity prices as well as fuel and EUA prices (Alberola et al. 2008). To control for temperature, I first create a weekly average of degree days for four major cities in the Nordic region: Copenhagen, Helsinki, Oslo, and Stockholm.[5] Then, to create a single degree day variable (DD_t), I take the population-weighted averages of the four individual degree day series.

Figure 1 provides plots of the prices along with a plot of $level_t$, and summary statistics for all variables are given in Table 2. From the top panel of Figure 1, two features of the EUA price series are easily observable. The first is the severe drop in EUA price near April 2006, and the other is that the EUA price approaches zero near the end of 2007, then abruptly shifts up to around 20€/ton. This pattern is due in part to the implementation design of the EU-ETS.

The EU-ETS was introduced in phases. Phase I ran from 2005–2007 and is commonly referred to as the "warm-up" or "Pilot" phase. Phase II runs from 2008–2012. Phase II has stricter emissions reduction targets and covers more installations than Phase I. Within a phase, installations may bank any unused annual permits for use in later years of that phase. However, banking between Phase I and Phase II was prohibited. The price drop in April 2006 came in response to early emissions verifications from several countries that suggested there was an overallocation of allowances.[6] Since banking was not allowed between phases, prices continued to slide as Phase I drew to a close and it became evident that there was a surplus of allowances. After Phase I ended, EUA prices immediately jumped up to reflect the stricter emissions reduction targets of Phase II. Figure 1 provides several other readily observable aspects. First, it is apparent that the electricity price increases in August and September of 2006 coincide with a drop in reservoir heights from their historical levels over that time, which lends support to the use of the *level* variable in this study. Also, the rise in electricity prices near the end of 2007 appears to happen concurrently with rising natural gas and coal prices during that time.

[5] Degree day is defined in this study as the absolute value of the difference between observed average daily temperature (degrees Fahrenheit) and 65. Temperature data for each of the cities were obtained through the publicly available University of Dayton's Average Daily Temperature Archive (http://www.engr.udayton.edu/weather/). This degree day variable is the sum of heating and cooling degree days.

[6] Beginning on April 24, 2006, five E.U. member states (The Netherlands, Czech Republic, France, Sweden, and Belgium) revealed that their 2005 emissions were far lower than their granted allowances.

While it is informative to visually inspect the data in order to gain intuition about the relationships among the various series, much more can be gained from a rigorous statistical analysis of the system. There are many different ways the relationships in this system could be estimated. Instead of modeling all of the intricate relationships among these price and nonprice variables explicitly, however, the data-driven vector autoregressive (VAR) model is used. Several features of the VAR model make it appropriate in this context. First, VARs allow for the estimation of a reduced-form dynamic relationship among a system of endogenous variables, conditional on exogenous variables, with a limited number of user-defined restrictions required. As discussed originally in Sims (1980), the lack of user-imposed restrictions is desirable in complex systems. Dynamic considerations are also important in explaining the relationship among the prices of EUAs, combustion fuels, and electricity, as shown in the related empirical work referenced above. Second, price variables often exhibit dynamic behavior consistent with nonstationary, I(1) processes. Not accounting for these I(1) variables can lead to spurious regression results, and removing the nonstationarity by first differencing the I(1) variables can delete informative long-run, cointegrating relationships. VARs can easily be amended to handle cointegrated I(1) variables in what is commonly referred to as a cointegrated VAR (CVAR) or as a vector error correction model (VECM). CVARs provide a convenient way to parameterize both short-run and long-run dynamics of a system [see Johansen (1996) for details]. Finally, from the estimation of VARs and/or CVARs, impulse response functions (IRFs) can be estimated. IRFs show how a shock to a given endogenous variable impacts the expected future values of the variables in the system. In the context of this study, it can be seen through the IRF how a shock to EUA prices impacts electricity prices while accounting for the interactions and feedbacks such a shock may have on related fuel prices.

The estimation method proceeds as follows. First, preliminary tests are conducted to test for the order of integration in the univariate series. Second, assuming that the tests conclude at least some of the series are I(1), the cointegrating rank of the I(1) variables is determined. Once the cointegrating rank has been determined, a CVAR model is estimated. After the CVAR model is estimated, an impulse response analysis is conducted to determine how innovations to the EUA price are propagated through the system, and in particular how they affect electricity prices on both the short- and long-term horizons. Results of this procedure are given in the next section.

4. Results and Discussion

4.1 Preliminary Tests

Testing for the order of integration in individual series has long been standard practice in applied time series econometrics, and hence many unit root (UR) tests exist. Traditional Augmented Dickey Fuller (ADF) tests and the more efficient Dickey Fuller–Generalized Least Squares (DF-GLS) test of Elliott et al. (1996) are computed. These tests are applied to each of the price series and to the *reservoir level* variable.[7] From the data plots, it appears P^g has some potential temporary outliers and P^{EUA} has an obvious level shift when Phase II begins. Franses and Haldrup (1994) have shown that ADF-based UR tests, such as the DF-GLS test, often overreject the null in the presence of "temporary change" outliers and level shifts. To account for these outliers and the level shift, the UR with breaks test of Lanne et al. (2002) is also used. For each of the P^g series the UR with breaks test is conducted with an endogenously chosen impulse outlier, and for the P^{EUA} series the test is run with a level shift. Results of the tests are given in

Table 3.

For the ADF tests, all series fail to reject the null of a UR for both specifications tested. With only a constant included in the auxiliary regression, all price series, except for natural gas, fail to reject the null of a UR based on the DF-GLS tests. The *level* variable does narrowly reject the null of a UR at the 10 percent significance level. With a linear trend and a constant included, tests for all series fail to reject the null of a UR. However, no linear trend is apparent in any of the series. When an endogenously chosen impulse outlier is included in the UR tests for P^g the null of a UR is not rejected. The same is true when accounting for the level shift in P^{EUA}. Evidence provided in these tests shows clearly that the price series P^{elec}, P^c, and P^{EUA} are best modeled as I(1). The results are mixed for P^g and *level*. The UR tests corrected for outliers indicate that P^g has a UR. Since the natural gas price series has obvious outliers, it seems likely that test not accounting for outliers will be biased. Therefore, this study proceeds under the assumption that P^g is an I(1) process. The DF-GLS tests narrowly reject the nonstationary null for *level* at the 10 percent significance level, but standard ADF tests indicate a UR. Furthermore, the degree of endogeneity for this variable is unclear. If hydroelectricity is used strategically to

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[7] While $level_t$ is by construction a mean reverting process, for a given historical mean and for a fixed sample the series may exhibit properties that suggest nonstationarity. Thus, unit root (UR) tests are conducted for this series. UR tests for DD_t are excluded here because, as expected, the variable follows an easily discernable seasonal pattern and thus does not display any stochastic trending behavior.

capture higher electricity prices, *level* may be endogenous. On the other hand, if the reservoir levels are primarily determined by weather conditions, *level* is best modeled as an exogenous variable. For these reasons, this variable is modeled in two separate ways. In Model 1, $level_t$ is considered as an endogenous I(1) variable. In Model 2, $level_t$ is considered as a stationary exogenous variable.

Given the order of integration of the variables used, a general VECM specification can be formulated:

$$\Delta Y_t = \alpha\beta' Y_{t-1} + \sum_{i=1}^{k-1} \Gamma_i \Delta Y_{t-i} + \Phi Z_t + \delta D_t + \varepsilon_t \tag{1}$$

where under Model 1:

$$Y_t = \begin{bmatrix} P_t^{elec} \\ P_t^{g} \\ P_t^{c} \\ P_t^{EUA} \\ level_t \end{bmatrix},\ Z_t = \begin{bmatrix} DD_t \\ DD_{t-1} \end{bmatrix},\ D_t = \begin{bmatrix} D1_t \\ D2_t \\ D3_t \end{bmatrix},\ \varepsilon_t = \begin{bmatrix} \varepsilon_t^{elec} \\ \varepsilon_t^{g} \\ \varepsilon_t^{c} \\ \varepsilon_t^{EUA} \\ \varepsilon_t^{level} \end{bmatrix}$$

and for Model 2:

$$Y_t = \begin{bmatrix} P_t^{elec} \\ P_t^{g} \\ P_t^{c} \\ P_t^{EUA} \end{bmatrix},\ Z_t = \begin{bmatrix} level_t \\ DD_t \\ level_{t-1} \\ DD_{t-1} \end{bmatrix},\ D_t = \begin{bmatrix} D1_t \\ D2_t \\ D3_t \end{bmatrix},\ \varepsilon_t = \begin{bmatrix} \varepsilon_t^{elec} \\ \varepsilon_t^{g} \\ \varepsilon_t^{c} \\ \varepsilon_t^{EUA} \end{bmatrix}.$$

In (1), β is the $(p \times r)$ cointegrating vector that determines the r long-term relationship(s) between the p I(1) series, and α is the loading matrix that determines how the endogenous variables respond to disequilibrium(ia) in the long-run relationship(s). The rest of the right-hand side of (1) describes the short-run dynamics. Because no linear trend in the variables is discernable, right-hand side constants are neglected and the exogenous variables in Z_t are demeaned.[8] In addition to the lagged, differenced endogenous variables and the exogenous

[8] Constants were also excluded from the cointegrating vector because cointegration vector parameter restriction tests described in Johansen (1996) indicate the constant can be excluded from the cointegration space.

variable of Z_t, the model also includes three impulse dummies.[9] The first of these dummies, $D1_t$, controls for the April 2006 EUA price drop, and the other two variables, $D2_t$ and $D3_t$, control for the change from Phase I to Phase II.[10] Finally, the vectors ε_t are the unmodeled innovations to the system such that $\varepsilon_t \sim N(0,\Omega)$ and $\mathrm{cov}(\varepsilon_t,\varepsilon_s)=0$ for $t \neq s$.

To determine the cointegrating rank, r, a Johansen trace test based on the maximum likelihood approach of Johansen (1991) is used.[11] Test statistics for the trace test, denoted LR, are given in

Table 4. For the Model 2 specification the results clearly indicate the existence of a single long-run relationship. The results from the trace statistic that $r = 1$ are not as strong for Model 1, but still show signs of a single long-run relationship. The paper proceeds under the result that both model specifications have a single cointegrating vector.

4.2 VECM Estimation

With the cointegrating rank determined, the parameters of (1) can be estimated. To do this, a maximum likelihood estimation approach is used. For each specification, the lag selections [k in (1)] are chosen from Schwarz information criterion (SIC) minimization and the cointegrating vector β normalized on P_{t-1}^{elec}. Results from the estimation for Models 1 and 2 are given in Tables 5 and 6, respectively.

The cointegrating vector estimates from both model specifications show that the signs of the long-run relationship are economically sensible. From the short-run parameters, it can be seen that short-run dynamics of electricity prices are driven primarily by natural gas and EUA prices as well as reservoir levels and temperature. The signs of these interactions are consistent

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9 Seasonal dummies are excluded from the models because in both cases they were found to be largely insignificant. While seasonal variation is likely present in the data, the insignificance of the seasonal dummies is likely due to the fact that they are superfluous because most of the seasonality is being picked up by the variable DD_t.

10 The verification date for 2007 emissions occurred midweek for the week ending December 7, 2007. Therefore, the EUA price jump from the end of Phase I to the beginning of Phase II actually occurs over two periods given the way the data are aggregated for this study. This creates the need for two dummy variables to account for the transition from Phase I to Phase II.

11 Generally the inclusion of exogenous variables Z_t creates nuisance parameters in the limiting distribution of the trace test. However, as pointed out in Rahbek and Mosconi (1999), when $\alpha_\perp^{'}\Phi = 0$, where $\alpha_\perp$ is such that $\alpha_\perp^{'}\alpha = 0$, then no nuisance parameters are present. Based on the estimation results presented below, $\alpha_\perp^{'}\Phi = [0.01 \ \ -0.01]'$ for Model 1 and $\alpha_\perp^{'}\Phi = [-0.08 \ \ 0.01 \ \ 0.05 \ \ -0.01]'$. Given that these vectors are near zero, the critical values presented in Johansen (1996) are used without corrections.

with economic theory for both specifications. For Model 1, the short-run dynamics of the other price series and $level_t$ are determined largely by their own autoregressive components, but some interrelationships do exist. First, the short-run dynamics of natural gas prices have significant reactions to coal prices, but the coal price series does not react significantly to natural gas price fluctuations.

Second, EUA prices have a significant negative reaction to increasing degree days.[12] At first, this result may seem counterintuitive since larger degree days are associated with a greater demand for energy and, thus, increased CO_2 emissions. However, as pointed out in Alberola et al. (2008), the sign of temperature-related variables such as degree days depends on deviations from the variable's seasonal means. Therefore, if the DD_t variable is representative of a larger E.U.-wide degree day variable and on average below the long-run expected degree days value, the sign of the DD_t parameter in the P_t^{EUA} equation would be negative. Indeed, by using temperature data from 1995 through 2007 to construct the long-run average weekly degree days variable as described above, I do find that on average the series DD_t is lower than its long-run average. Lagged EUA prices also appear to have a significant negative effect on reservoir levels. This is as expected since increased EUA prices would create a greater reliance on emission-free generation technology such as hydroelectricity.

Finally, in contrast to Bunn and Fezzi (2007), the system approach used here finds no significant interaction between EUA prices and input fuel prices.[13] In addition, it appears from the parameter estimates of α and loading parameter restriction tests described in Johansen (1996) that $level_t$ and P_t^c are weakly exogenous. For $level_t$ this may be expected since there are many exogenous forces that determine reservoir height that are not modeled here. In the case of P_t^c this is also expected since coal is traded globally and thus may be driven more by forces outside of this regional model.

For Model 2, the short-term dynamics results are similar to those in Model 1. The cointegrating vector estimate is also similar across specifications, further enforcing the idea of a

[12] The fact that the parameter value of DD_{t-1} is positive and of the same absolute value as the parameter on DD_t suggests, as expected, that temperature fluctuations have only a temporary effect on EUA and electricity prices.

[13] Input fuels have been found to be price drivers in other studies of EUA price formation [e.g., Mansanet-Bataller et al. (2007) and Alberola et al. (2008)]. However, the results of these studies are not directly comparable to those presented here because those studies do not use system estimation techniques, but rather single-equation estimation methods.

more exogenously determined *level*$_t$ variable. One readily apparent difference between the two specifications is that, unlike in Model 1, P_t^c is not weakly exogenous in Model 2.

Residual analysis is conducted for model diagnostic testing. Based on the Portmanteua test, Model 1 specification fails to reject the null of no autocorrelation in the residuals at the 5 percent level with 16 lags included, while Model 2 specification fails to reject the null for this test at the 10 percent level. Lagrange multiplier tests for autocorrelation, which are more appropriate for checking autocorrelation at shorter lags, reveal that Model 1 specification fails to reject the null of no autocorrelation at the 5 percent level for up to two lags, while Model 2 specification fails to reject the null at this significance level for up to six lags. For both specifications, residuals show signs of nonnormality and autoregressive conditional heteroscedasticity (ARCH). However, as shown in Gonzalo (1994), maximum likelihood estimates in a cointegration analysis are still consistent even with these issues. Model selection criterion was also conducted to compare the two models. Based on the Akaike information criterion (AIC), SIC, and Hannan-Quinn criterion, the Model 2 specification is preferred to Model 1.

4.3 Impulse Response Analysis

While the parameter estimates of the VECM are informative in terms of deciphering what statistically significant relationships exist, interpreting these coefficients can be difficult due to the intricate interaction among variables. For example, determining the effect of a 1€ increase in EUA price on Elspot electricity price is more complicated than simply calculating the marginal response based on the parameter estimates from the first line of Equation (1), because that would neglect any further feedback that changes in these variables may have on the system dynamics as a whole. To account for these more complicated interactions, impulse response analysis is often conducted in conjunction with CVAR models to better understand how the movement in one variable affects all endogenous variables in the system. An IRF works by initially imposing a one-time innovation to one of the endogenous variables via the error term ε_t in (1). The effect of this shock on all the endogenous variables is then traced out over time based on the system dynamics estimated in the CVAR and assuming no other innovations hit the system. It should also be noted that since the endogenous variables of a CVAR model are I(1) variables, a one-time unit innovation in one of these variables would create a permanent one-unit increase, assuming no other interaction dynamics and no other innovations. Therefore, the innovation acts like a marginal change to the variable in question.

Because the focus of this paper is to determine how Nordic electricity prices react to changes in EUA prices, impulse response analysis is conducted with innovations entering through ε_t^{EUA}. IRFs were constructed for both model specifications. To account for contemporaneous correlation in the error terms, the innovations are orthogonalized through the generalized IRF (GIRF) procedure of Pesaran and Shin (1998). This orthogonalization procedure is used because it has the advantage of being unaffected by the order of endogenous variables in Y_t. Plots of the GIRFs using the average weekday wholesale electricity price for P_t^{elec} and scaled to a 1€ innovation in P_t^{EUA} are given in Figures 2 and 3 for Models 1 and 2, respectively. As can be seen from Figure 2, only electricity prices show any sizeable short-term response to innovation, increasing by 0.87€/MWh one period after the initial 1€-EUA price jump. As the responses are forecasted farther into the future, the permanent increase in electricity prices dampens, while reservoir heights decrease from historic levels and coal prices increase. Natural gas prices rise only slightly in response to an increase in EUA prices. Figure 3 displays a similar pattern to that in Figure 2, although the response of electricity prices to the EUA price shock (0.69€/MWh one period after the shock and 0.32€/MWh 30 periods after the shock) are not as great. This is as expected because, as seen in Figure 2, when $level_t$ is modeled as an endogenous variable it decreases in response to the EUA price shock, which has a positive feedback into electricity prices. When $level_t$ is modeled exogenously, as in Model 2, this positive feedback no longer exists, so electricity prices will not increase by as much as in Model 1.

The shape of the GIRFs for electricity prices displays some intuitive economic relationships. Given an inelastic short-term demand for electricity, a shock to an input price such as EUAs is likely to be met with a rapid increase in electricity prices. This increase would be expected to subside to some degree over time as demand for electricity, as well as demand for the fuels used for electricity generation, adapted to the higher prices. The impulse response of electricity prices for both models conforms to this line of reasoning.

The values of the impulse response estimates for electricity prices also appear to be sensible. As mentioned above, if electricity generators fully pass through the opportunity cost of holding permits and demand elasticity remains constant, then the marginal response of electricity price to a 1€/ton increase in CO_2 prices should be approximately 0.85€/MWh if a coal-fired generator is at the margin and 0.48€/MWh if a natural gas turbine is at the margin. The short-term electricity price response estimates are 0.87€/MWh and 0.69€/MWh for Models 1 and 2, respectively. These estimates are thus in line for a market where coal-fired generators are usually on the margin and CO_2 costs are fully or near fully passed through. Given the competitive nature of the Nordic electricity market and this market's electricity generation profile, this description is appropriate for the Nordic electricity market.

For the most part, the shape of impulse responses for the input fuels also appears intuitive. The higher price of CO_2 emissions should increase the demand for hydroelectricity and to some degree the demand for natural gas. Therefore, as shown in Figure 2, it is expected that $level_t$ would decrease and P_t^g would increase, as shown in Figure 2 andFigure **3**, with a positive EUA price shock. Since the use of natural gas for electricity generation is relatively low in the Nordic region, it is not surprising that this increased demand for this cleaner fuel has only a small positive effect on natural gas prices at the Zeebrugge hub. The estimated response of coal prices does not appear quite as intuitive. Given the greater CO_2 emissions intensity of coal, it is expected that coal prices would react negatively to an increase in EUA prices. Initially, the GIRF for both models predicts such behavior. However, over a longer period, the effect of the initial shock to P_t^{EUA} leads to slightly positive effects on coal prices in both model specifications. This is due to the estimated positive, although small and statistically insignificant, impact of EUA prices on coal prices from the CVAR models. Indeed, when bootstrapped confidence intervals are calculated for the GIRFs, the long-term response of coal prices to a EUA price shock is not statistically different from zero at traditional levels of significance. Furthermore, in conditional subset VECM models not shown here, the impulse response of P_t^c to a P_t^{EUA} shock was found to be essentially zero at all time periods. These results of limited response of P_t^c to P_t^{EUA} shocks are as expected given the more global nature of coal trading compared with EUA trading.

4.4 Varied Response

The results presented above are derived from an electricity price that is an average of all weekday hourly wholesale prices. However, as shown in Table 1, several different generating fuels, with varying associated CO_2 emissions, are used in the Nordic region. It would stand to reason then that the response of electricity prices to price shocks in EUAs will vary in this region as the input fuel used by the marginal, and hence price-setting, generator varies. Unfortunately, the data set used in this study does not allow one to observe the generation fuel used by the marginal generator. Instead, different electricity price series are created based upon different subdivisions of the hourly wholesale electricity price data, which are likely to be representative of prices resulting from varying marginal generators. A separate CVAR is then estimated for each of these electricity price series such that P_t^{elec} in Models 1 and 2 is represented by these new electricity price series. From the estimated CVARs, separate impulse response analyses are conducted to see how the responses to shocks in the EUA market vary across the different electricity price series.

This study considers two different subdivisions of the electricity price data. In the first subdivision, denoted as the "hour average electricity price," a separate electricity price series is made by taking the weekday average of electricity prices for each hour of the day. That is, the hour one electricity price series is simply the average price of the first hour's price from each of the five weekdays (Monday through Friday), and this averaging technique is used for each of the 24 hours. This subdivision strategy was used because for most weekdays the hourly electricity load curve, and hence the marginal generator, follows a generally stable pattern. This load curve is typified by low electricity demand in the early morning (hours 1–7) and late evenings (hours 20–24), and higher demand during the hours between these troughs with peaks during midmorning hours (hours 8–10) and hours directly at the end of the working day (hours 18–19). Thus, it is expected that low-load periods will be supplied by electricity generated from low marginal–cost fuels such as hydro, nuclear, and coal, while high-load periods will require production from higher marginal–cost fuels such as natural gas.

Figure 4 gives a plot of the maximum responses of electricity prices to a 1€ price jump in EUAs for each of the 24 hour average electricity price series.[14] In all cases this maximum response was, as expected, a near immediate response, happening one period after the initial shock. The top panel gives the responses based on the Model 1 specification, while the bottom panel gives the Model 2 responses. The plots are again similar in shape, and again both plots have an economically intuitive form. As expected, the price series from off-peak periods, where the price-setting generator is likely to be a more carbon-intensive coal-fired plant, show higher responses to CO_2 price shocks. The price series from peak-demand periods, where the marginal generator is more likely to be a less carbon-intensive natural gas turbine, show markedly lower responses to EUA price shocks. Furthermore, the estimated responses appear to be economically sensible given complete or near-complete pass-through EUA prices. The off-peak responses are in the range of approximately 0.80€/MWh–0.95€/MWh for Model 1 and approximately 0.60€/MWh–0.75€/MWh for Model 2; both responses are near the 100 percent pass-through

[14] Confidence intervals shown in Figures 4 and 5 are derived by using the bootstrapping method, with standard percentile intervals, described in Lütkepohl (2005).

response of 0.85€/MWh expected for coal generators.[15] Conversely, peak-period responses are in the range of approximately 0.65€/MWh–0.70€/MWh for Model 1 and 0.40€/MWh–0.50€/MWh for Model 2, near the 0.48€/MWh response expected if there is 100 percent pass-through of CO_2 costs for markets with natural gas generators at the margin.

For the Nordic region, the daily load curve may not be stable throughout the year due to the region's long summer days and short winter days. Therefore, the peak periods in a day may change throughout the year. This may bias the hour average electricity prices in terms of trying to find price series indicative of various marginal producers. The second subdivision of electricity prices, denoted as the "sorted hour average electricity prices," attempts to circumvent this varying peak periods problem. For this grouping of electricity prices, in each day the hourly electricity prices are first sorted from low to high. Then, a weekday average is constructed for each of the 24 "sorted" hours of the day. That is, a given data point for the first sorted hour average electricity price is an average of each weekday's lowest hourly price. The logic behind this subdivision is that the hourly prices for any given day should be representative of the hourly demand for that day and could therefore more accurately display which hours should be assigned as peak and off-peak.

Figure 5 displays the plots of the maximum responses of electricity prices to a 1€ price jump in EUAs for each of the 24 sorted hour average electricity price series. Again, these maximum responses all happen near term, occurring in either the same or subsequent period as the EUA price innovation. These plots reveal that for approximately 14 of the lowest-priced hours of the day, the electricity price response to P^{EUA} price shocks is fairly constant and relatively high. These response estimates are near the off-peak response estimates from Figure 4 for both Models 1 and 2. Beyond the 14 lowest-priced hours, the electricity price response begins to taper off, suggesting a change in the marginal producer at these points. Furthermore, the responses based on the highest-price hours for both Models 1 and 2 are lower than the response estimates presented in Figure 4. This is somewhat expected. However, price response estimates for these peak price periods are still sensible given near 100 percent pass-through for natural gas turbines at the margin.

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[15] The Model 1 responses are slightly higher than those of Model 2 because Model 1 incorporates a feedback effect of reduced reservoir levels due to the increasing EUA prices.

5. Conclusion

This study uses a CVAR approach and impulse response analysis to determine the relationship between electricity prices and EU-ETS CO_2 permit prices for the Nordic electricity market. By using weekly average input and electricity prices, the results show that Nordic electricity prices react significantly to price shocks in EUAs in the short-term, but that this response dampens over time. It is also shown that the relevant fuel prices of natural gas and coal react slowly and minimally to EUA price shocks.

By exploiting the hourly prices given in the data set used here, this study also finds evidence of time-varying electricity price responses to EUA price shocks. These results show that short-term responses of off-peak electricity prices to EUA price shocks are significantly higher than those of peak electricity price periods. Furthermore, short-term electricity price responses estimated from the impulse response analysis are in line with expected responses for markets where CO_2 costs are near fully passed through. This suggests that the Nordic electricity market is operating as a competitive market.

From a policy perspective, the estimated short-term responses of electricity prices to EUA price shocks suggest that the CO_2 market has created a wealth transfer from electricity consumers to electricity producers. This would then appear to support those calling for at least a partial auctioning of allowances to the electricity production sector. However, longer-term responses indicate that high levels of CO_2 emissions cost pass-through cannot be maintained. This, as alluded to above, could be the result of a demand response and/or a supply response. Acknowledging this difference between short- and long-term responses perhaps calls for a second look at the meaning of pass-through and what these dynamic properties of electricity price responses to CO_2 emissions cost shocks mean in terms of developing allocation mechanisms.

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Table 1. 2005 Electricity Production Profiles

	Denmark	Finland	Norway	Sweden
Total (TWh)	34.4	67.9	138.0	154.7
Nuclear	0.0	22.3	0.0	69.9
Coal	14.5	7.0	0.0	1.1
Oil	0.3	1.5	0.0	1.4
Peat	0.0	4.5	0.0	0.1
Natural gas	8.6	8.9	0.4	0.7
Other thermal	0.2	0.0	0.0	0.6
Hydro	0.0	13.6	136.5	72.1
Wind	6.6	0.2	0.5	0.9
Bio	2.9	8.9	0.3	7.4
Waste	1.3	1.0	0.3	0.9

Table 2. Summary Statistics

Variable	Mean	Min.	Max.	Stnd. Dev.
P^{elec}	35.82	77.25	12.88	12.31
P^{EUA}	13.75	31.22	0.06	9.74
P^{c}	57.32	95.31	43.59	13.81
P^{g}	5.67	16.15	2.38	2.49
level	0.57	9.51	–22.73	8.30
DD	20.90	50.35	0.60	13.05

Note: P^{elec} is the price of electricity based on the average price of weekday hourly prices.

Table 3. Unit Root Tests

	ADF Tests		DF-GLS Tests		UR with Breaks Tests	
Variable	const.	const. & trend	const.	const. & trend	const.	break location
P^{elec}	–2.11	–2.07	–0.92	–1.78	–	–
P^{EUA}	–1.23	–1.23	–0.92	–1.31	–1.25	12/14/07
P^{c}	–0.20	–2.10	–0.58	–1.22	–	–
P^{g}	–2.41	–2.41	–2.07**	–2.30	–2.24	3/31/06
level	–1.67	–1.93	–1.63*	–1.69	–	–

Notes: **Significant at 5% level; *significant at 10% level. Lags chosen by SIC minimization. Critical values for UR with breaks tests are given in Lanne et al. (2002).

Table 4. Cointegration Rank Test

	LR Statistics	
H_0: r =	Model 1	Model 2
0	58.92*	49.36**
1	27.29	17.94
2	10.30	1.92
3	3.85	0.21
4	0.03	–

Notes: **Significant at 5% level; *significant at 10% level [from Table 15.1 Johansen (1996)].

Table 5. Model 1 VECM Parameter Estimates

Cointegrating Relationship

P_t^{elec}	P_t^g	P_t^c	P_t^{EUA}	$level_t$
1	–3.25	–0.30	–0.13	1.13
	(0.52)	(0.04)	(0.14)	(0.12)

Short Run Parameters

	ΔP_t^{elec}	ΔP_t^g	ΔP_t^c	ΔP_t^{EUA}	$\Delta level_t$
EC_{t-1}	–0.14**	0.01**	0.01	–0.05**	0.00
ΔP_{t-1}^{elec}	0.10	0.02	–0.01	0.00	–0.01
ΔP_{t-1}^g	0.58	1.01**	0.02	–0.02	–0.06
ΔP_{t-1}^c	0.10	–0.09**	0.67**	0.12	–0.04
ΔP_{t-1}^{EUA}	0.42**	0.00	0.05	0.41**	–0.13**
$\Delta level_{t-1}$	–0.58**	0.03	–0.12	0.01	0.57**
ΔP_{t-2}^{elec}	0.02	–0.02*	–0.02	0.01	0.01
ΔP_{t-2}^g	–0.93**	–0.53**	0.16	–0.19	0.06

ΔP^{c}_{t-2}	0.06	0.07*	–0.10	–0.08	0.05
ΔP^{EVA}_{t-2}	–0.29**	0.01	0.05	–0.31**	0.07
$\Delta level_{t-2}$	–0.12**	–0.02	0.02	–0.01	0.07
DD_t	0.31**	0.01	0.01	–0.03*	–0.07**
DD_{t-1}	–0.32**	–0.01	–0.01	0.03*	0.07**
$D1$	0.52	–1.47**	0.07	–9.12**	–0.36
$D2$	–0.74	–0.56	–0.13	9.43**	0.25
$D3$	–1.06	0.12	–0.80	10.42**	0.87

Notes: Standard errors in parentheses for cointegration vector. **Significant at 5% level; *significant at 10% level. EC_{t-1} refers to $\beta' Y_{t-1}$.

Table 6. Model 2 VECM Parameter Estimates

Cointegrating Relationship

P^{elec}_t	P^{g}_t	P^{c}_t	P^{EVA}_t
1	–3.25	–0.29	–0.11
	(0.52)	(0.04)	(0.13)

Short-run Parameters

	ΔP^{elec}_t	ΔP^{g}_t	ΔP^{c}_t	ΔP^{EVA}_t		ΔP^{elec}_t	ΔP^{g}_t	ΔP^{c}_t	ΔP^{EVA}_t
EC_{t-1}	–0.13**	0.02**	0.01	–0.05**	$level_t$	–0.94**	0.01	–0.06	–0.02
ΔP^{elec}_{t-1}	0.10	0.02	0.01	0.00	DD_t	0.24**	0.01	0.01	–0.03*
ΔP^{g}_{t-1}	0.49	1.00**	0.01	–0.03	$level_{t-1}$	0.80**	0.01	0.08	–0.02
ΔP^{c}_{t-1}	0.07	–0.09	0.66**	0.12	DD_{t-1}	–0.26**	–0.01	–0.01	0.03
ΔP^{EVA}_{t-1}	0.30**	0.00	0.04	0.40**	$D1$	0.27	–1.45	0.07	–9.12**
ΔP^{elec}_{t-2}	0.05	–0.02**	–0.01	0.01	$D2$	–0.60	–0.59	–0.18	9.40**
ΔP^{g}_{t-2}	–0.88**	–0.53**	0.16	–0.19	$D3$	–0.30	0.08	–0.75	10.40**

ΔR^{C}_{t-2}	0.10	0.07*	–0.10	–0.08
ΔR^{EUA}_{t-2}	–0.23**	0.01	0.05	–0.31**

Notes: Standard errors in parentheses for cointegration vector. **Significant at 5% level; *significant at 10% level. EC_{t-1} refers to $\beta' Y_{t-1}$.

Figure 1. Data Plots

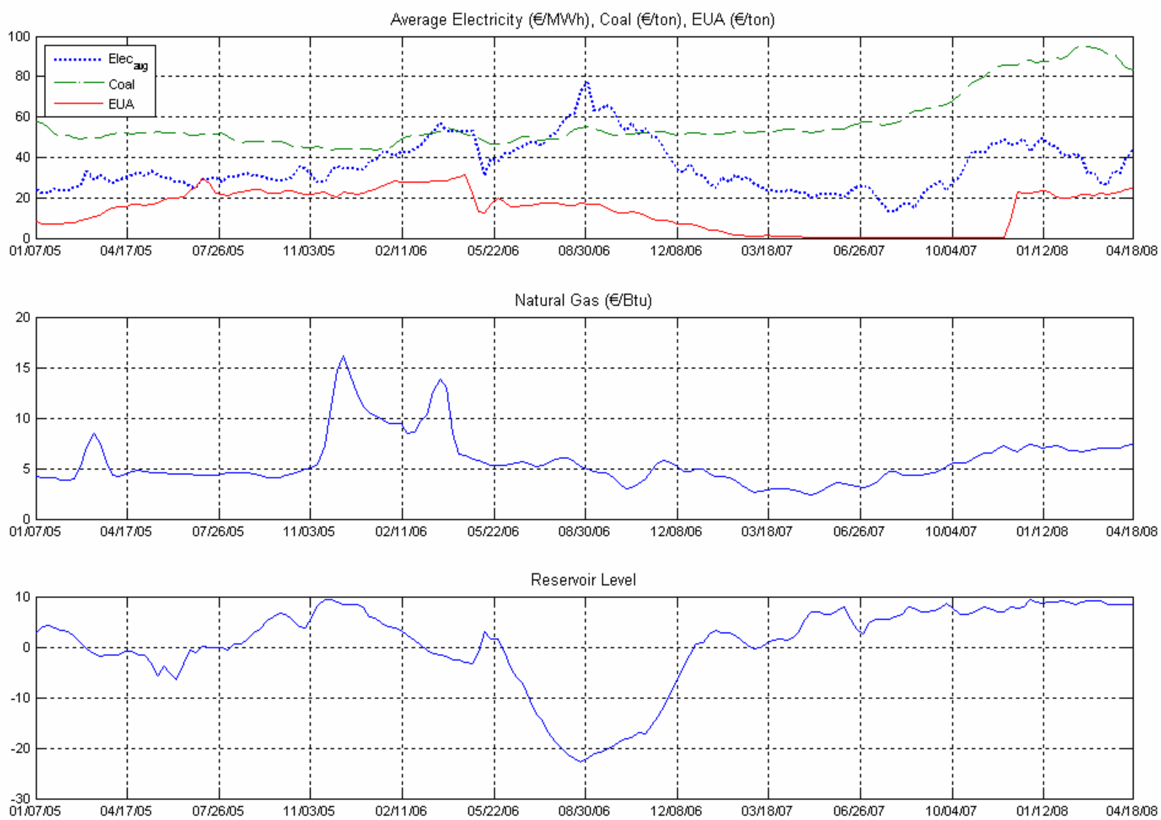

Figure 2. Model 1 GIRF for P^{EUA} Innovation

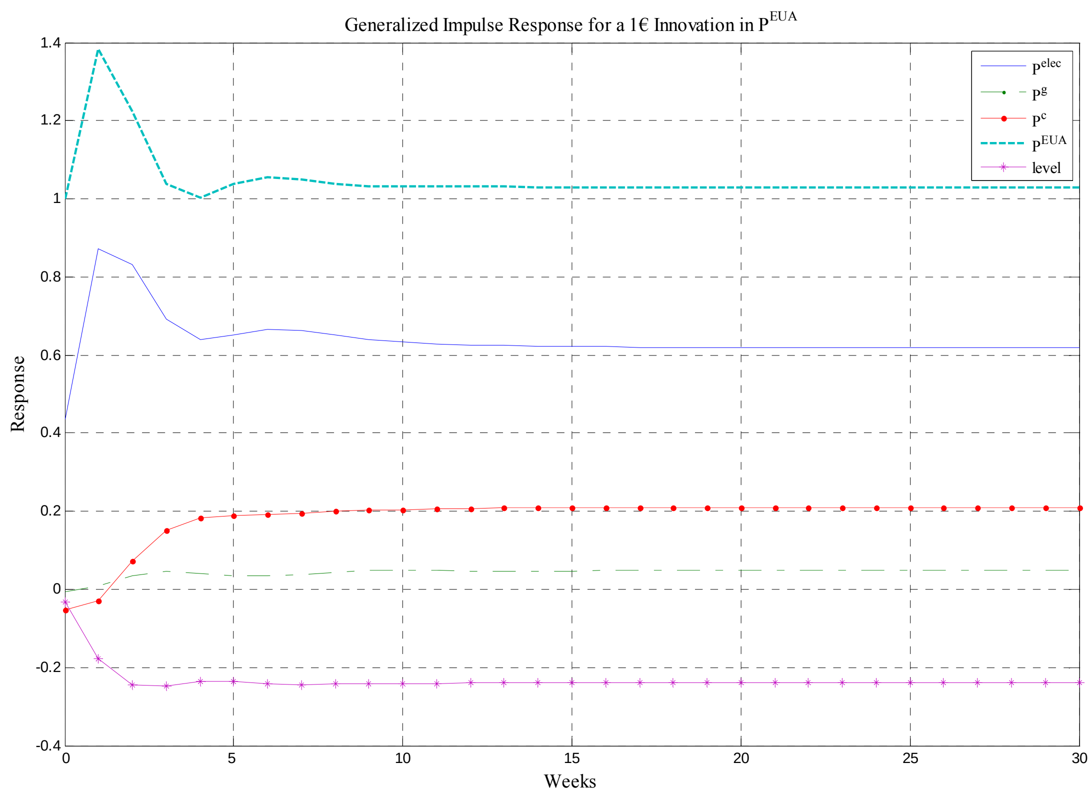

Figure 3. Model 2 GIRF for P^{EUA} Innovation

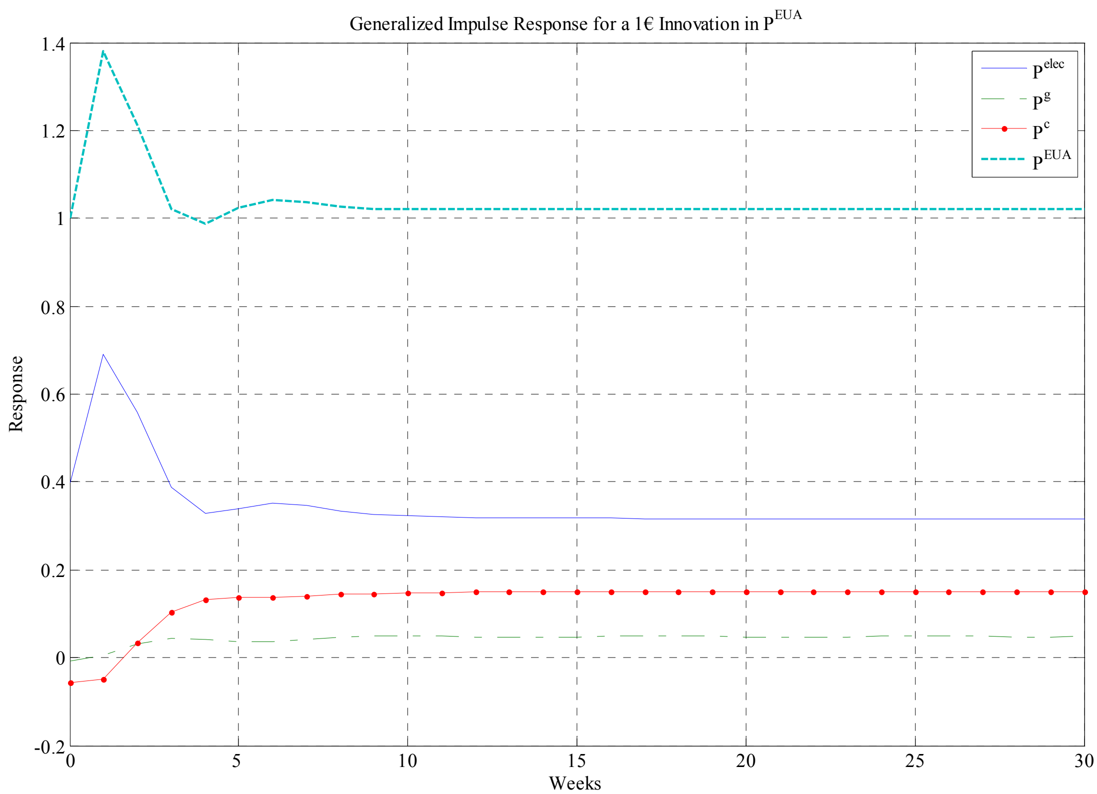

Figure 4. Short-Term Hour Average Electricity Price Responses to 1€-EUA Price Shock

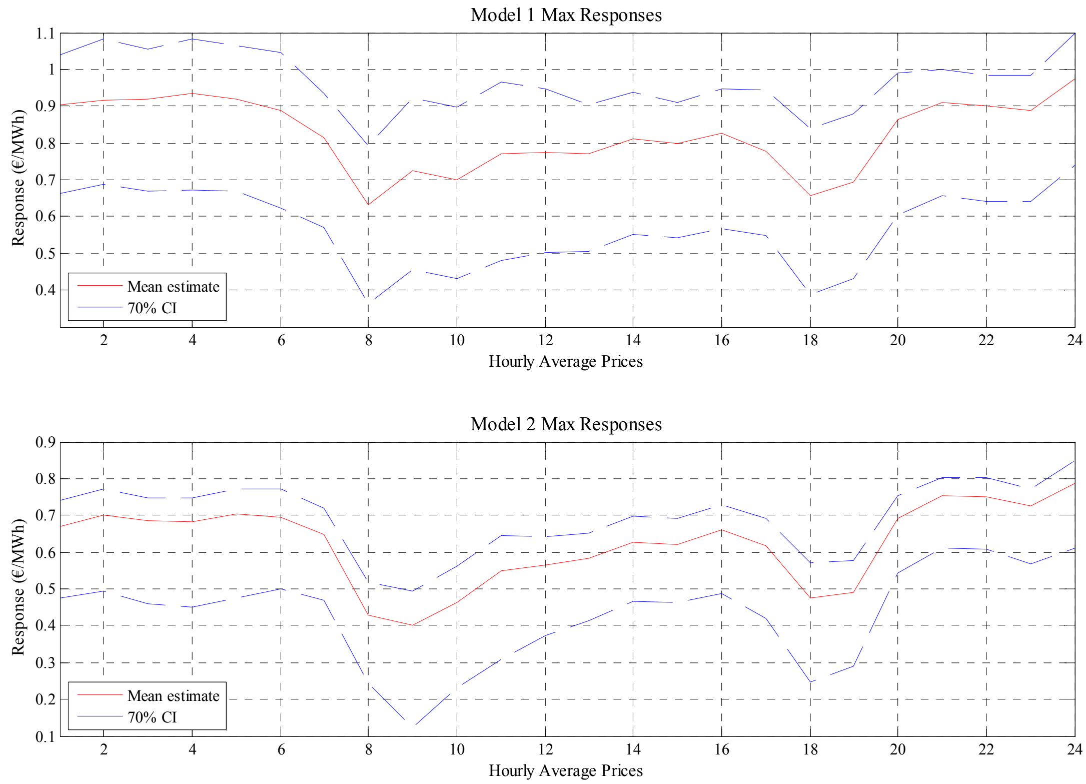

Figure 5. Short-Term Sorted Hour Average Electricity Price Responses to 1€-EUA Price Shock