Carbon content of electricity futures in Phase II of the EU ETS

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Abstract

We estimate the relationship between electricity, fuel and carbon prices in Germany, France, the Netherlands, the Nord Pool market and Spain, using one-year futures for base and peakload prices for the years 2009–2012, corresponding to physical settlement during the second market phase of the EU ETS. We employ a series of estimation methods that allow for an increasing interaction between electricity and input prices on the one hand, and between electricity markets on the other. The results vary by country due to different generation portfolios. Overall, we find that (a) carbon costs are passed through fully in most countries; (b) under some model specifications, cost pass-through is higher during peakload than during baseload for France, Germany and the Netherlands; and (c) the results are sensitive to the degree of cross-commodity and cross-market interaction allowed.

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1 Introduction

Thermal electricity from fossil sources generates CO_2 emissions as a by-product, and carbon policies aim to internalize the social cost of emissions by placing a price on them. If emissions are costly, they should be treated like any other input for electricity generation such as labor, capital and fuel. The costs of emitting CO_2 are thus passed through to the ultimate "polluters", i.e., the consumers who demand energy-intensive goods. The degree to which carbon costs are passed forward to electricity prices depends on market conditions (e.g. the degree of competition and consumers' demand response), and is important to determine the full distributional costs of climate policy, as well as its effect.

One important recent example where incidence effects gave rise to a heated debate is the "cost pass-through" discussion on EU ETS and electricity prices.[1] The debate started with a report by Sijm et al. (2006), which examines the electricity sector only and covers peak and base load pass-through estimates for Germany and the Netherlands using data for the first half year of 2005.[2] Sijm et al. (2008) extend the analysis to seven other EU ETS countries and a longer period. Both studies find positive pass-through rates for most countries, which is consistent with the interpretation of carbon as an opportunity cost.

The approach taken in these studies consists in applying a relatively simple econometric OLS framework to electricity spreads, which implies a series of restrictive assumptions. First, the price-setting generation technology is imposed *a priori* by using either the dark or the spark spread, although the true marginal generator may change every hour. This introduces a measurement error to the extent that the true marginal generator differs from the one used to compute the spread. Second, this type of analysis imposes a complete pass-through of fuel costs while estimating the degree of carbon cost pass-through, thus creating an artificial distinction among inputs of production. Third, it does not allow for interactions between

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[1]The European Union introduced the EU Emissions Trading Scheme (ETS) in 2005, which places a cap on aggregate emissions from the most energy-intensive industrial sectors. In the first two market phases, firms received allocations mostly at no cost. The general public took issue with the fact that firms raised their output prices despite free allowance allocation, reaping so-called "windfall profits". Providing allowances for free implies that the polluters receive the scarcity rent, whereas sound reasons exist to distribute these rents differently (Bovenberg and Goulder, 2000).

[2]Smale et al. (2006) focused on the other sectors covered by the EU ETS and found positive but smaller cost pass-through rates that varied with the degree of a sector's exposure to competition from firms outside the EU. Due to transmission constraints, outside competition is almost zero for the power sector.

prices for electricity, input fuels and carbon; and fourth, it assumes that carbon costs are passed through either immediately or within a short time period.

It is likely that electricity and input prices are determined jointly. For instance, an increase in carbon prices may (over time) lead to a shift from coal to gas generation. This decreases the demand for coal and increases that for gas, thereby increasing the gas/coal price ratio. At the same time, the increase in electricity prices will lead to a decrease in demand in the long run, which in turn can impact the demand for CO_2 permits and for input fuels. This interdependency may lead to complex and possibly prolonged adjustments in the system of prices to a shock in a particular variable. We address this by applying a vector error correction model (VECM) framework that has a dependent variable vector which includes electricity prices, emission allowance prices, and other relevant input prices.

Several papers have addressed the issue of cost pass-through by means of a cointegration framework. Fezzi and Bunn (2010) use a structural VECM that jointly models UK electricity, natural gas prices, and EU-ETS allowance (EUA) prices over Phase I of the EU-ETS. Their results imply that electricity and input prices are in fact cointegrated and find that a 1% increase in EUA prices led to a 0.32% long-run increase in U.K. electricity prices. Similarly, Fell (2010) carries out a VECM analysis of the Nordic electricity market (Nord Pool) for the years 2005-2008 using a dependent variable vector that includes prices for hourly spot electricity, natural gas, coal, and EU-ETS allowances (EUAs). He reports theoretically-consistent cost pass-through rates in the short-term, but also pronounced differences between short-term and long-term price adjustments.

Zachmann and von Hirschhausen (2008) also use a cointegration framework, though in a single-equation form rather than a VECM, using futures data for 2005-2006. They argue that carbon costs are passed through asymmetrically in Germany: the response to an increase in carbon prices had an immediate positive effect on electricity prices, but carbon price decreases did not elicit an electricity price response of the same magnitude. Extending the analysis to France, Belgium and the Netherlands for the period 2007-2010, Lo Prete and Norman (2013) again find evidence of cost pass-through, but not of asymmetry.

While these papers focus on estimations for separate electricity markets, Bosco et al. (2010) provide evidence that electricity prices are cointegrated *across* national markets. This

suggests that an assessment of carbon cost pass-through in a multi-country framework may be warranted. To allow for such cross-market relationships, we use a VECM that includes one-year futures for electricity (baseload and peakload) as well as input prices and a set of control variables. We focus on electricity markets in Germany, France, the Netherlands, Nord Pool and Spain (abbreviated as DE, FR, NL, NP, and ES, respectively). A second contribution lies in our focus on market data for the delivery period November 2009-2012 (more precisely, on one-year futures between November 2008 and December 2011), making our paper one of the first studies that measures the post financial crises impact of Phase 2 of the EU ETS on electricity prices exclusively.[3] This examination of more recent data also allows us to see how the fast growth in renewable energy, particularly in Spain and Germany, may affect cost pass-through.

The major drawback of a multi-country, multi-commodity cointegration framework is its complexity. The impact of a shock in one variable on all other variables in the system is determined by the interaction of a series of parameters and has to be estimated using impulse-response functions (IRFs), but little economic interpretation (and therefore intuitive verification) can be attached to a single parameter estimate (see Lütkepohl, 2005). At the same time, VECMs tend to be sensitive to the choice of lags of the underlying vector autoregressive process and other specifications. The combination of high complexity and sensitivity to parameter choices implies caution in the interpretation of the results. For this reason, we also estimate cost pass-through using somewhat simpler autoregressive conditional heteroskedasticity (ARCH) approaches that treat fuel and CO_2 prices as exogenous to the electricity price. We believe that by combining the results from all models, we obtain a better understanding of the underlying processes than by relying on one estimation method alone.

We find that carbon costs are passed through to electricity futures, that electricity and input prices are cointegrated, and that there appear to be further cointegrating relationships between electricity prices of adjacent markets. The results also show how sensitive cost pass-through estimates are for model specification. In the specifications that do not allow for

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[3]Lo Prete and Norman (2013) study cost pass-through in Phase II of EU ETS by analyzing data over the period July 2007 - June 2010. Our study differs from theirs in that they are focused on asymmetric pass-through, relying on single equation error correction models, while we use multiple estimation techniques and do not consider asymmetric pass-through. We also find evidence for a structural break in some of the series around 2008 and therefore focus on data that start after the financial crises.

cross-market relationships, we find that the CO_2 price affects electricity prices even more during peakload than during baseload in some markets, although the difference is not always statistically significant. This is surprising, because the lower carbon intensive gas plants have traditionally been the marginal generators during peak demand periods and, thus, we would expect a lower response to carbon price movements during peakload. These findings change considerably in the multi-country cointegration framework. In particular, if we allow for market cointegration, the results are more in line with expectations in that base load pass-through is greater than that of peakload. However, pass-through rates for both baseload and peakload for many markets in the multi-country framework are somewhat higher than expected.

In the next sections, we describe the theoretical relationship between carbon and electricity prices and present our methodology and data. Section 5 contains our results, and Section 6 concludes.

2 Theoretical framework

We start by showing the theoretical relationship between input and electricity prices. In a competitive wholesale electricity market, the electricity price is equal to the marginal cost of generation for the marginal generator, which is usually fossil-based. Let R refer to the residual demand for fossil-based electricity, which is total demand net of generation by technologies other than coal, oil and natural gas. Residual demand is a function of exogenous factors X (such as economic activity, temperature and the availability of renewable energy), and it will depend on prices for electricity at least in the long run, and possibly also on fuel and allowance prices:

$$R = r(P, F, A; X) \tag{1}$$

where P, F and A refer to the price of electricity, fuel and allowances, respectively, and $r(\cdot)$ can be interpreted as the ordinary demand function. The supply of fossil-based electricity has to equal its demand. This establishes a relationship between electricity prices, input prices

and demand:

$$P = p(F, A; X) = K(R) + F \cdot \eta(R) + A \cdot \psi(R) \tag{2}$$

with R defined by (1). K refers to the per-unit cost of labor, capital and other non-fuel costs, η is the heat rate (MWh of fuel per MWh of electricity) and ψ is the emission intensity (CO_2/MWh), all of which depend on the identity of the marginal generator and thus on residual demand. The interpretation of $p(\cdot)$ is that of the marginal cost function or inverse supply function.

We define cost pass-through as the total effect of an exogenous shock in the allowance price on the electricity price. Totally differentiating (2), setting $dF = dX = 0$, and rearranging (see Appendix) leads to:

$$\frac{dP}{dA} = \frac{\psi + p_R \cdot \frac{\partial R}{\partial A}}{1 - \eta \frac{\partial F}{\partial P} - \psi \frac{\partial A}{\partial P} - \frac{p_R}{P_R}} \tag{3}$$

$$\text{with} \quad p_R \equiv \frac{\partial p}{\partial R} = \frac{\partial K}{\partial R} + \frac{\partial \eta}{\partial R} F + \frac{\partial \psi}{\partial R} A \quad \text{and} \quad P_R \equiv \left(\frac{\partial R}{\partial P} \right)^{-1}$$

where p_R and P_R represent the slope of the inverse supply and demand functions for electricity, respectively. Equation (3) describes the equilibrium effect of an exogenous change in the allowance price on the electricity price, allowing for indirect effects via demand and prices. The first term in the numerator is the direct effect, which corresponds to the emission intensity of the marginal generator. The second term describes the indirect effect that arises if allowance prices affect residual demand for electricity (but *not* via an increase in electricity prices). Finally, the denominator captures the feedback effect: A change in the electricity price may affect fuel prices and the allowance price, as well as consumer demand for electricity (last term), all of which in turn affect the electricity price.

Expression (3) implies that the identification of any individual channel of cost pass-through is extremely challenging. For instance, the dependencies of non-fuel costs K, heat rates and carbon intensity on residual demand that are needed to determine p_R are unknown and may vary with the level of residual demand. Likewise, the relationship between the vari-

ous prices may not be constant over time and depend on price levels as well as factors outside the model, such as global demand for coal or natural gas. Last but not least, (3) refers to the equilibrium response of electricity prices to a shock in the allowance price, but it says nothing about the pattern of adjustments over time.

In order to deal with these difficulties, researchers make simplifying assumptions with various levels of stringency. When specifying their estimation strategies, Sijm et al. (2008, 2006) implicitly assume that residual demand is independent of allowance and fuel prices ($\partial R/\partial A = 0$) and that there is no feedback effect via a change in allowance and fuel prices in response to a change in the electricity price ($\partial F/\partial P = \partial A/\partial P = 0$), which reduces (3) to

$$\frac{dP}{dA} = \psi \cdot \frac{P_R}{P_R - p_R} \qquad (4)$$

This is also the assumption underlying our ARCH approach. Note that if demand is completely inelastic, or supply perfectly elastic, (4) collapses to ψ.

In our VECM approach, we allow the electricity price to influence input prices via the feedback effects in the denominator, and all endogenous variables to adjust to each other over time. Even though the coefficient estimates from the cointegration framework do not directly correspond to (3) because it is an inherently dynamic approach, and the individual components cannot be identified (e.g., the response of demand to a change in the allowance price), the long-run value of the impulse-response function is a reduced-form estimate for (3).

It should also be noted that the model presented above assumes perfect competition. A number of simulation studies have studied carbon cost pass-through under different market structures (e.g., Lise et al. (2010) and references therein). With imperfect competition, prices exceed marginal costs by a markup which depends on residual demand. In the Appendix, we show that in this case, cost-pass through will be less than (3), because some of the EUA cost increase is absorbed by the markup. To what extent the assumption of perfect competition in the wholesale electricity market is representative for the countries and period that we study in detail is not known.[4] Examining the potential for market power is beyond the scope of

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[4]Under perfect competition, cost pass-through is independent of the method of permit allocation. If firms perceive market power in the permit market and take the permit-output market interaction into account, the choice of allocation will influence the market outcome (Hintermann, 2011).

this study and not easily estimated given our data. However, in the Appendix, we augment the model above to include a degree of market power. The results from this expanded model imply that one should observe lower carbon-cost pass through in the presence of market power.

3 Empirical strategies

3.1 ARCH models

If we assume that input prices are exogenous to electricity prices and each other, the most natural way to estimate cost pass-through is to regress electricity prices from each market separately (P_t^i) on prices for coal (C_t), natural gas (G_t) and CO_2 allowances (A_t). To allow for non-immediate adjustment, we include current as well as lagged input prices up to order q_C, q_G and q_A, respectively. We use the following regression specification:

$$
\begin{aligned}
P_t^i = &\sum_{i=0}^{q_G} g_i G_{t-i} + \sum_{i=0}^{q_C} c_i C_{t-i} + \sum_{i=0}^{q_A} a_i A_{t-i} \\
&+ \beta_0 + \beta_1 t + \beta_2 Res_t + \beta_3 FTSE_t + \beta_4 M_t + \gamma^n P_{t-1}^n + \epsilon_t \\
&\text{with} \quad E[\epsilon] = 0; \quad \text{Var}[\epsilon_t] = \sigma_t^2 = \delta_0 + \delta_1 \epsilon_{t-1}^2
\end{aligned}
\tag{5}
$$

As additional control variables, we include a trend, current reservoir levels Res_t (where applicable) and country-specific FTSE indices, which proxy for economic activity and thus for demand. In addition, we include a set of monthly dummies M_t to adjust for the seasonality of expected electricity demand. To allow for cross-market links, we include lagged neighboring electricity prices P_{t-1}^n in some regressions (we define neighbors as countries sharing a border). The lags are necessary to avoid an endogeneity problem, because unlike in our VECM approach, the explanatory variables in (5) have to be predetermined. Since all price series in our sample have unit roots, we take first differences of all variables.[5] Finally, we

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[5]We tested for stationarity using the augmented Dickey-Fuller test (with the null hypothesis of a unit root), as well as the KPSS test (with the null hypothesis of stationarity). Both tests are consistent with a unit root. Note further that if all included variables are cointegrated, it is not necessary to first-difference the data, since a linear combination of the variables will be stationary. Our cointegration tests indicate that electricity and input prices are indeed cointegrated, but some of the other included variables may not be.

allow for "fat tails" in the distribution of price changes by using an autoregressive conditional heteroskedasticty (ARCH) specification.

We estimate (5) separately by electricity market and load period (base vs. peak). Equilibrium cost pass-through for fuel and allowance prices is given by the sum of the coefficients on current and lagged prices, and we focus on these sums for the remainder of the paper. Because non-significant lags would cause the estimate for total pass-through to be very imprecise, we start with two lags for all input prices and eliminate lags by stepwise reduction until the highest lags are significant at $p < 0.05$.

3.2   Single-country vector error-correction models (VECM)

Unlike the ARCH methods used above that require first-differencing the series to remove stochastic trends, cointegration analysis searches for common stochastic trends among the series, such that linear combinations of the variables result in stationary series. The cointegration analysis thus determines whether the examined price series move together (i.e., if they share a common trend). Furthermore, through the VECM estimation, we do not impose exogeneity of the input prices as was done above.

We estimate the cointegration model using a VECM of the form

$$\Delta y_t = \Pi y_{t-1}^\star + \sum_{k=1}^{K} \Gamma_k \Delta y_{t-k} + \gamma X_t + \epsilon_t \tag{6}$$

where y_t is a vector of the prices (electricity, natural gas, coal, and EUA). The parameter vector Π is defined as $\Pi = \alpha'\beta$, with β being the cointegrating vector describing the long-run relationship between the variables, and α is the loading matrix that determines the speed of adjustment from the long-run relationship. The vector $y^\star$ is defined as $y_{t-1}^\star = [y_t\,1]'$ with "1" included so that a constant is added to the cointegrating relationship. Δy_{t-k} is the kth lagged first-difference of y_t with Γ_k as the corresponding matrix of parameters. In the estimation procedure, K is chosen by a model selection criterion, namely Bayesian information criterion minimization. X_t is a vector of exogenous variables with parameter vector γ. For X_t, we use the same set of exogenous variables as discussed above, namely $X_t = [Res_t, FTSE_t, M_t]$. Finally, the disturbance vector ϵ_t is assumed to have a normal joint distribution with means

of zero and a variance-covariance matrix of Ω.

We start by using a cointegration framework for single markets, before extending it to multiple electricity markets. We first determine the cointegrating rank (i.e., number of cointegrating relationships) embodied in β. The rank is determined using the Johansen trace and maximum-eigenvalue tests (for details, see Johansen, 1995).[6]

3.3   Multi-country VECM

As noted above, there could be inter-country correlations present that are not explicitly accounted for in the individual country results. Such correlations may bias the results presented in the country-by-country analyses given above. We therefore consider systems where instead of looking for cointegrating relationships between a single country's electricity price and natural gas, coal and EUA prices, we add multiple electricity price series along with the natural gas, coal, and EUA prices to the y_t vector. With multiple electricity prices in the y_t vector, interactions across prices from the various included electricity markets are allowed in several ways.

First, the short-run dynamics captured by the off-diagonal elements of Γ_k can allow for one country's current electricity prices to react to changes in other countries' prices. Second, off-diagonal elements of Ω allow for shocks in one country's electricity price to transmit to other countries. Third, if the countries' electricity prices have independent long-run relationships with the input prices, then non-zero off-diagonal elements of the loading matrix α can create a situation where a given country reacts to the long-run disequilibrium in another country's long-run relationship. Finally, there may be situations where each country does not have an independent long-run relationship between its electricity price and the input prices. That is, in a y_t vector that includes N electricity prices and the input prices, we may find a cointegrating rank less than N, resulting in a likely triangular representation in which multiple electricity prices are in the same long-run relationship.

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[6]To choose the lag length for the lagged, first-differenced vector of dependent variables needed in the auxiliary regression, we used the BIC model selection criteria.

4 Data

All regressions are based on weekly averages of 1-year future prices for electricity, coal, gas and EUAs. Using futures allows us to exclude contemporaneous shocks that affect electricity spot prices both on the demand side (e.g., temperature and economic activity) and on the supply side (e.g., wind, sunshine, rainfall or policy decisions). We focus on weekly averages in order to reduce noise relative to daily data, while keeping the degrees of freedom high relative to monthly data.

Most exchanges offer contracts for peak electricity (defined as 8 a.m. to 8 p.m. during work days) and base electricity (average of all hours), but not for individual hours. Since the marginal generator generally differs every hour, the estimated cost pass-through is based on the average pass-through of the marginal generators throughout the year. This complicates the interpretation of the coefficients, since the frequency during which the different generation technologies are on the margin is not known. For example, consider the carbon intensity of a coal-fired power plant of (roughly) 1 tCO_2/MWh, and that of a gas-fired plant of about 0.4 tCO_2/MWh. If we measure a cost pass-through of, say, 0.7€/MWh (meaning that a 1-€-increase in the allowance price leads to an electricity price increase of 0.7 €/MWh in equilibrium), this could be consistent with a situation where coal and gas are both on the margin for 50% of the time and firms are able to fully pass through their carbon costs to consumers, but also one where coal is always on the margin and firms are only able to pass on 70% of carbon costs. Using more finely defined periods would allow for a more homogeneous technology on the margin and thus lead to cleaner results, but at the cost of having to control for all contemporaneous shocks that also determine electricity prices.

Using futures data causes a second and somewhat more subtle complication. The estimated cost pass-through is based on the average pass-through of the *expected* marginal generator. Presumably this expectation is based on past observations, but traders may also take into account the evolving generation capacity profile of the market, which is difficult to incorporate properly.[7]

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[7]Spot and futures prices for electricity differ not only in variance due to contemporaneous shocks, but comparing 1-year futures prices with the corresponding spot price one year later implies a futures premium of around 15% for baseload for all countries in the sample, and around 30% for peakload in DE, FR and NL and 12% in NP. Since electricity cannot be stored, the difference must be due to cost hedging.

We use one-year electricity futures from the German (DE), French (FR), Dutch (NL), Nord Pool (NP) and Spanish (ES) markets, along with futures prices for coal, gas and CO_2 allowances. We run all analyses separately for baseload and peakload futures, because the generation technology and thus the carbon intensity can be expected to differ.[8] Although we collected futures prices from 2007-2011 (corresponding to delivery in 2008-2012), we decided to restrict the analysis to the period after the financial crisis due to convergence issues and empirically determined structural breaks in the electricity price series.[9] Our sample period covers future prices starting in 2008, week 46 through the end of 2011, corresponding to a delivery period of November 2009 through December 2012.

We use continuous one-year coal futures based on the the API#2 index traded on the European Energy Exchange (EEX), because it is the most-quoted standard for hard coal entering Northwestern Europe.[10] For natural gas, we use continuous one-year futures from the Title Transfer Facility (TTF), and for EUA futures we use December 2012 contracts from EEX. We accessed all price data through Thomson Reuters Datastream.

Finally, we included hydro reservoir data to allow for the possibility that a very full or very empty reservoir today may impact the next calendar year's electricity prices. We obtained reservoir level data from country providers.[11]

Figure 1 shows total annual generation by energy source for our five markets. The generation portfolios are quite heterogeneous and also differ somewhat between peakload and

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[8]A baseload one-year future contract refers to the continuous supply of electricity during the following calendar year; the standard contract size of 1 MW therefore translates to a contract volume of 8,760 MWh. Peakload futures refer to the electricity supply between 8 a.m. and 8 p.m. on weekdays, with a contract volume of 3,132 MWh. All contracts in our sample are settled financially, based on the difference between the agreed price and the average spot price during the respective delivery period.

[9]We tested for a structural break in the context of our ARCH framework. In the VECM framework, we find that by including data prior to the financial crisis the impulse response analysis leads to responses that do not stabilize at some value, regardless of forecast window or lag specification. Such a result might be expected for data that is integrated of order two or has large discontinuous jumps. To avoid such complications, we restrict our data to the post-financial crisis period.

[10]The API#2 index is a CIF ARA price reference for coal imported into Europe and is the average of the Argus assessment and the McCloskey European steam coal marker. CIF is an acronym for cost, insurance and freight and means that the seller assumes the cost of shipment including insurance until the port of destination, and ARA stands for delivery in Amsterdam, Rotterdam or Antwerp. By continuous futures we mean individual annual futures contracts rolled over on a monthly basis, as provided by Datastream. Current market data is publicly available at www.eex.com. Finally, to be in the same €/MWh units as the natural gas futures price, we convert the coal price into a €/MWh value. Assuming an average 25.46 MegaJoules/kilogram (MJ/kg) energy content for Australian coal (see www.coalmarketinginfo.com/coal-basics) and $2.78E^{-4}$ MWh/MJ, we apply a 7.07 MWh/ton conversion factor to get coal prices in €/MWh.

[11]Available at www.nordpoolspot.com (Nord Pool area), www.rte.fr (France) and servicios3.marm.es (Spain); last accessed in April 2013.

Figure 1: Electricity generation by energy source by country and year, 2008-2012

Generation by energy source, all hours[a]

Generation by energy source, peakload[b]
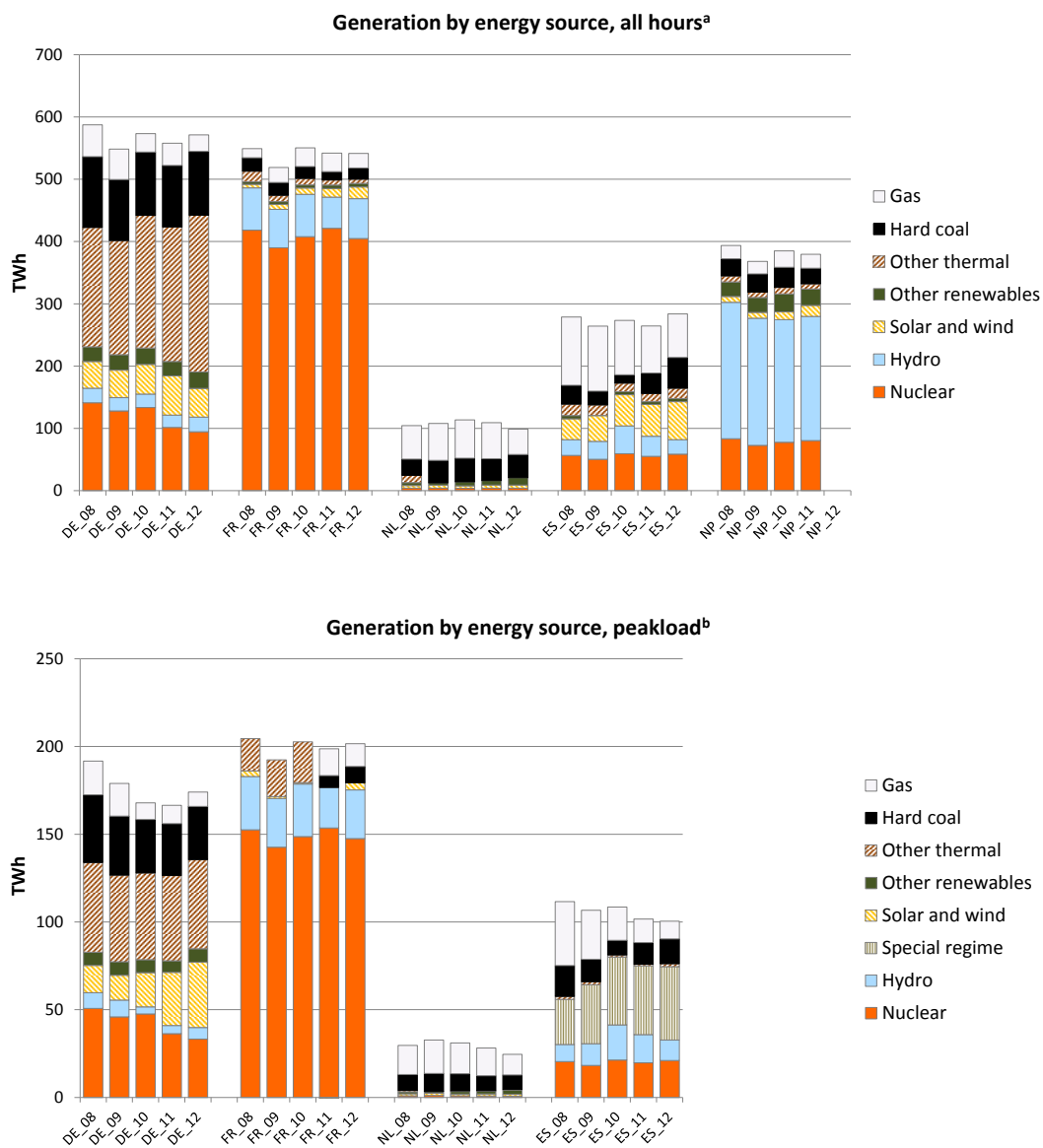
a: Source: Own graph based on monthly data from ENTSO-E and country TSOs. "Other thermal" refers to lignite and oil; b: Source: Own graph based on hourly data from Thomson Reuters Point Connect and country TSOs. "Special regime" in Spain refers to renewables and cogeneration; "other thermal" in FR_08-FR_10 includes coal and natural gas because the hourly French data does not differentiate between thermal sources prior to 2011; hourly production data not available for Nord Pool area.

baseload. Whereas Germany, the Netherlands and Spain rely mostly on thermal generation from fossil fuels, France produces most of its electricity using nuclear energy, and the Nordic area using hydro generation. Generation by renewables other than hydro has increased in recent years, especially in Germany and Spain. Figure 2 shows that this is due to a massive expansion of solar and wind generation capacity in those countries, whereas the installed capacity of the other energy sources remained largely stable.

Figure 2: Installed generation capacity (end of year)
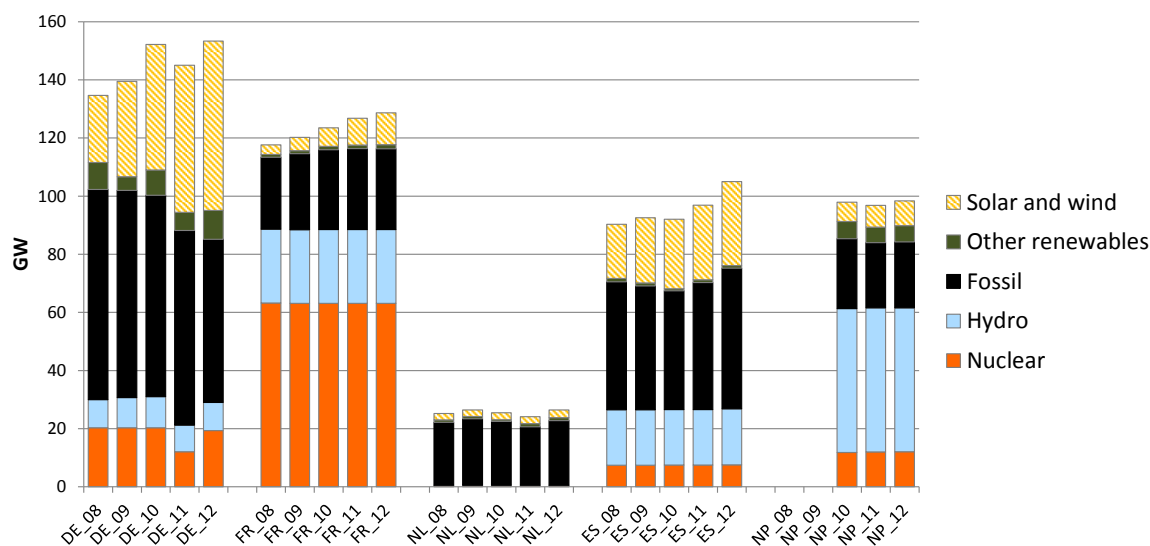
Source: Own graph based on data from ENTSO-E

Note that the identity of the marginal generator does not directly follow from the generation portfolios. For example, nuclear power in France is (presumably) priced according to the fossil generator that would replace it, even if this generator is not running.[12] Also, since these countries are interconnected, it is possible that the price in one market is set by the marginal technology in another. Table 5 shows transmission capacities between the markets in our sample, both in terms of direct connections as well as indirect connections via third countries such as Belgium (connecting NL and FR), Denmark (connecting NP and DE) and Switzerland (connecting FR and DE).

Figure 3 displays the electricity futures for baseload (5 markets) and peakload (4 mar-

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[12]The output of nuclear plants can be varied depending on the reactor design, and French reactors have the ability to adjust output within a certain range such that nuclear is the marginal generation technology during at least some hours of the year (Pouret et al., 2009). However, since the cost structure of nuclear generation features large investment and very low marginal production costs, and since EdF holds a monopoly of nuclear plants in France, French nuclear plants are unlikely to price according to marginal cost.

Table 1: Transmission capacity in 2012 in MW[a]

Exp \ Imp	Belgium	France	Germany	Netherlands	Nordpool	Spain	Switzerland	Sum
Belgium	n/a	800		946				1'746
France	3'150	n/a	1'967			1'450	3'100	9'667
Germany		2'483	n/a	2'449	1'300		953	7'185
Netherlands	946		2'166	n/a	700			3'812
Nordpool			1'286	700	n/a			1'986
Spain		408				n/a		408
Switzerland		1'663	4'000				n/a	5'663
Sum	4'096	5'354	9'419	4'095	2'000	1'450	4'053	30'467

a: Source: Year-ahead data from ENTSO-E; where unavailable (DE-CH & DE-NL) we used day-ahead capacity for June 1, 2012 instead.

kets) for our sample period. Future prices are closely correlated, especially for Germany, France and the Netherlands, with somewhat lower prices in Spain (baseload prices available only) and Nord Pool. Especially peak prices for DE, FR and NL are very similar, whereas NP peak futures are significantly lower. This implies binding transmission constraints between the Nordic and continental European markets during peakload, which is consistent with the limited transmission capacity shown in Table 5.

Figure (4) shows input prices (EUA, coal and gas) along with German power futures. The figure provides a visual indication of cointegration across and within markets, which is confirmed by our cointegration tests.

Figure 3: Year-ahead futures for baseload (left) and peakload (right) electricity
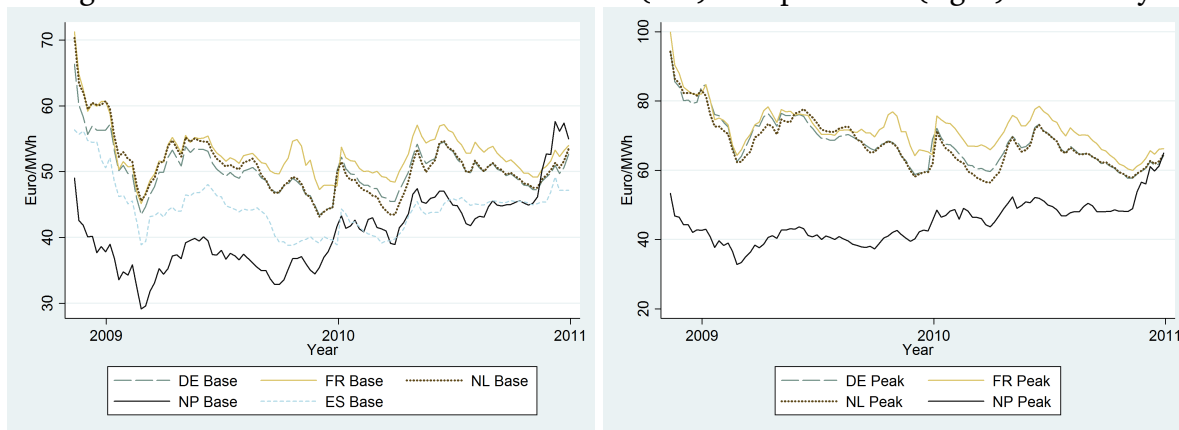

The electricity markets in our sample are connected by transmission lines, which have a limited capacity. Figure 5 shows the share of hours in 2012 during which the transmission constraints were binding between any two adjacent regions (for the Nordic region, transmission data is given on the subregional level). The figure shows that the capacity constraint for

15

Figure 4: Prices for gas, allowances, coal and German power
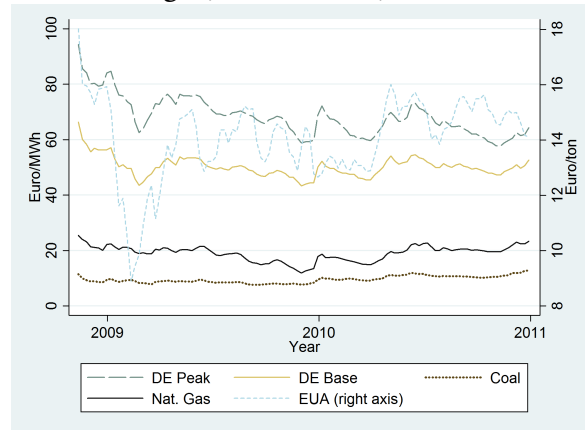
exporting German power to France and the Netherlands is binding much more frequently than the constraint to import from these countries, whereas the Nordic region is mostly export-constrained. The fact that transmission constraints are binding during a significant share of the time at all borders, but never all the time, implies that electricity prices in adjacent markets should be cointegrated sometimes, but not always. This provides justification for both our single-country and the multi-county approaches.

Figure 5: Transmission constraints in 2012
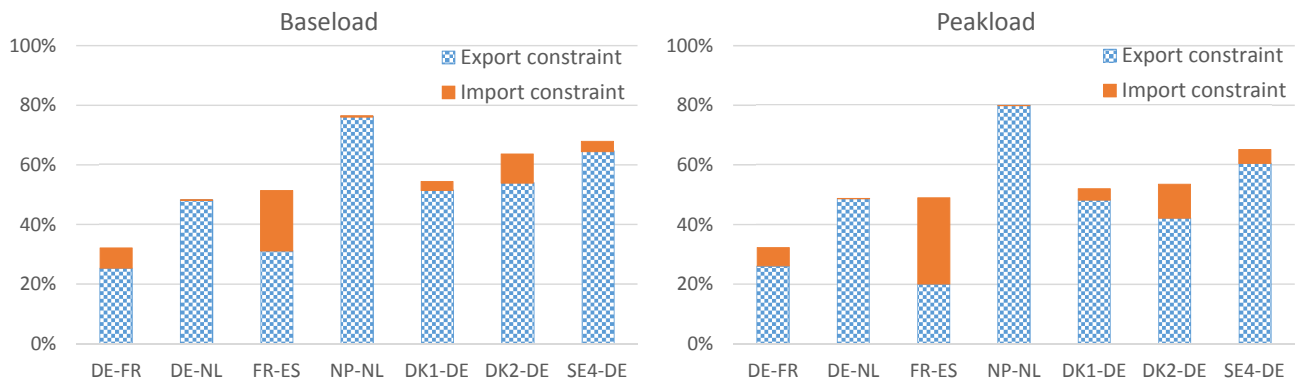
Note: Export means transmission from the region mentioned first to the one mentioned second; for example, an export constraint for DE-FR means that transmission from Germany to France is at maximum capacity, whereas an import constraint refers to the reverse direction. DK1 and DK2 refer to Denmark electricity regions 1 and 2, respectively; SE4 is Sweden's region 4. The Netherlands are linked by submarine power cable to Norway. Source: Own graph based on ENTSO-E data.
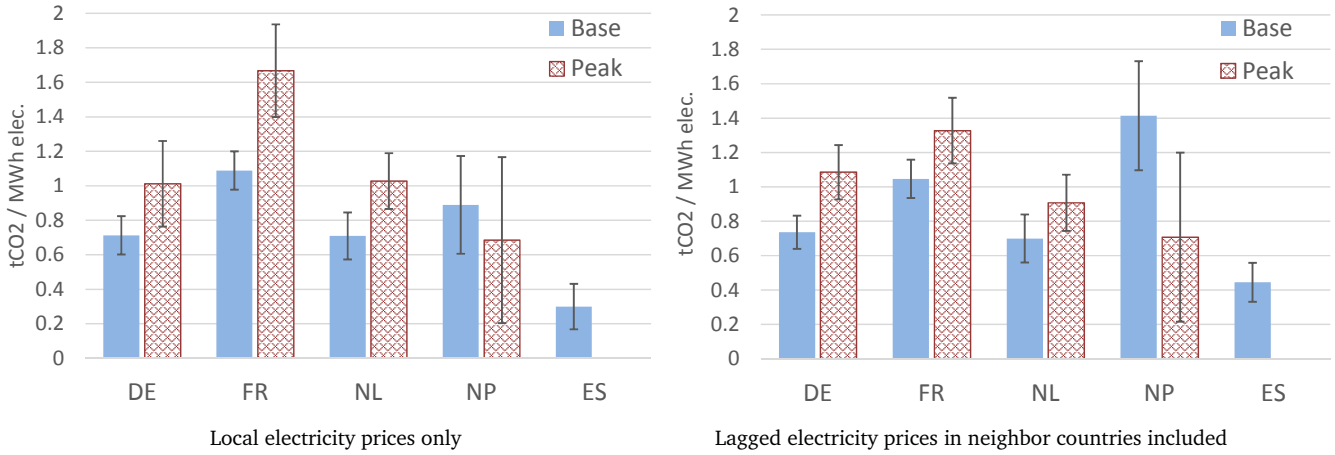
5   Results

In the following, we present the results from the models presented in Section 3.

5.1 Cost pass-through with exogenous input prices

The left panel of Figure 6 shows the marginal effect of the allowance price on electricity 1-year-futures for the five markets in our dataset as estimated using (5) when no cross-market interactions are allowed ($\gamma^n = 0$), whereas in the right panel we relax this restriction. The columns refer to the point estimates for $a \equiv \sum_i a_i$, and the error bars are the bounds of a 95% confidence interval.

Figure 6: Marginal effect of the EUA price on electricity prices

Local electricity prices only   Lagged electricity prices in neighbor countries included

To put our results into perspective, recall that with marginal cost pricing, exogenous input prices and no demand responses, full cost pass-through of carbon costs occurs when a is equal to the average emission intensity of the marginal generators during the respective load period (base or peak). The carbon intensity is around $0.96 tCO_2/MWh$ for a coal plant, $0.6 tCO_2/MWh$ for an open-cycle gas turbine (OCGT) and $0.42 tCO_2/MWh$ for a combined-cycle gas turbine (CCGT). Most countries show baseload responses between 0.7 and 1.1 tCO_2/MWh, which is generally in the range of expectations and implies that coal is on the margin during a significant number of hours. The exception is Spain, which has a lower average emission intensity consistent with its higher share of gas generation.

Since peakload generation is generally assumed to be less carbon-intensive than baseload due to a higher gas share, we would expect the carbon content to be lower as well. However, this does not appear to be the case in Germany, France and the Netherlands, where the effect of the allowance price on peakload prices is higher than on baseload, and the difference is significant at p<0.05 for the latter two. These anomalous results are softened, but do not

disappear when we control for cross-country interactions as shown in the right panel (the difference is now statistically significant for Germany, but not for France and the Netherlands). These results suggest that cross-country interactions do indeed matter. For most countries, allowing for cross-market effects moves the estimates closer to expectations.

Figure 7: Marginal effect of fuel prices on electricity prices
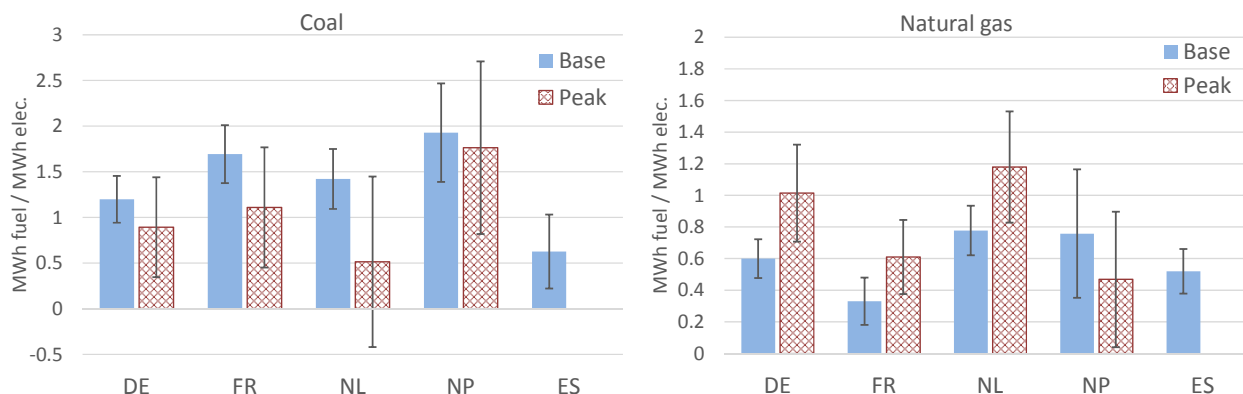
Note: Lagged electricity prices in neighbor countries included for both fuel types

One possible explanation for the high carbon cost pass-through during peakload could be an increase in renewable capacity in recent years. Because renewables have very low marginal costs, an additional GWh of renewable generation decreases residual demand for thermal electricity one-to-one. If renewable generation drives gas out of the system during peakload as suggested by Figures 1 and 2, coal may be increasingly on the margin during peakload.[13] However, the sensitivity of electricity prices to coal and gas prices as shown in Figure 7 do not clearly back up this hypothesis: Based on the point estimates, coal appears to be on the margin more often during baseload than during peakload (because the electricity price is more responsive to the coal price during the former than the latter), whereas the opposite is true for natural gas. This suggests that the marginal generator during peakload should have, on average, a lower carbon intensity than during baseload, which is inconsistent with the results in Figure 6. Note, however, that the difference between the load periods is not statistically significant due to the large confidence intervals.

To interpret the magnitudes of fuel cost pass-through, we have to assume heat rates for

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[13]This can easily be imagined for Germany due its large wind and solar park, but even French gas may be driven out of the system during some hours. By 2012, France had an installed renewable capacity of around 12.3 GW (without hydro) as shown in Fig. 2, plus an import capacity of around 5.3 GW (Table 1), compared to an installed fossil capacity of 27 GW (coal and gas combined). Note further that due to transmission, the marginal coal generator that replaces gas may be located in another country.

18

the average marginal coal and gas generators; dividing the marginal effects in Figure 7 by these heat rates then yields an estimate for the share of hours during which each fuel source is marginal. For example, if the average marginal coal generator has a heat rate of 2.5 (meaning that 2.5 MWh of coal are needed to produce 1 MWh of electricity), a coefficient estimate for coal of 1.25 implies that coal is on the margin for 50% of the time. Our estimates therefore suggest coal shares between 25% (Spanish baseload) and 77% (Nordpool baseload). Likewise, using a heat rate for the average gas generator of 2.0, the gas shares implied by Figure 7 range from 17% (French baseload) to 59% (Dutch peakload). These imputed generation shares are not always as expected, in particular for German baseload where coal is generally assumed to be on the margin during most hours. Also, the imputed shares based on the point estimates do not add up to 100% for all countries, which would be expected under full pass-through of fuel costs (note that the confidence intervals are large enough such that a share of 100% is included). Overall, these results are not very convincing and could be an indication of model misspecification.

The coefficients on the additional control variables generally have the expected sign, but are significant only for some countries and load periods.[14] To test whether our model misses a variable that is both a determinant of electricity prices and correlated with input prices, we ran regressions that additionally included gasoil futures (there is some generation by oil), renewable generation and reservoir levels in neighboring countries, and stock price indices specific to the electricity sector. However, the qualitative nature of our results was unaffected.

Another possible source of model misspecification lies in the endogeneity of electricity and input prices as discussed before. If electricity and input prices are jointly determined, the coefficients from our ARCH approach could be severely biased. In the next subsections, we treat all price variables as endogenous.

5.2   Single-market cointegration results

Results from the Johansen trace and maximum-eigenvalue tests are given in Table 2. Because the conclusions drawn from the trace and maximum-eigenvalue tests are the same for this

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[14]The FTSE index was positive and significant at p<0.1 for Germany (both baseload and peakload) and for Dutch baseload. Reservoir levels were negative and significant for Spain only.

Table 2: Individual Country Cointegration Rank Test

	DE-Base	DE-Peak	NP-Base	NP-Peak	NL-Base	NL-Peak	FR-Base	FR-Peak	ES-Base
$r = 0$	62.9**	81.2**	58.4**	52.6**	76.6**	68.1**	76.0**	81.9**	62.9**
$r = 1$	21.5	28.6*	29.8	29.9*	25.9	26.5	23.0	23.0	31.6**
$r = 2$	9.9	10.5	12.3	11.4	11.8	11.7	12.2	12.6	10.4
$r = 3$	1.4	2.1	1.8	1.6	2.1	5.7	2.5	2.9	0.9

Note: The null hypothesis is rank$(\alpha\beta') \leq r$. "**" and "*" denote rejection of the null hypothesis at the 5% and 10% significance levels, respectively.

application, we report only the trace-test statistics. The results suggest that for most country-markets (base or peak) there appears to be a single cointegrating relationship among the electricity price and the input prices of natural gas, coal, and EUAs.[15] The exceptions are ES-Base and, at least at the 10 percent significance level, DE- and NP-Peak. These country-markets appear to have up to two cointegrating relationships among the four price series. These exceptions are somewhat perplexing. The results for DE-Peak, NP-Peak and ES-Base suggest that there is a cointegrating relationship between the given electricity prices and at least some of the input prices and another cointegrating relationship among the input prices. Given that the analyses of the other country-markets do not pick up such an input-price-only cointegrating relationship, it seems unlikely that it exists.[16] We therefore proceed under the assumption that each country-market has a single cointegrating vector among electricity, natural gas, coal, and EUA prices.

From the parameter estimates of the VECMs, we can estimate the response of electricity prices to a shock in EUA prices, accounting for the relationships across all prices in the system, through the use of impulse response analysis. There are several ways to compute impulse responses. We use the generalized impulse response form (GIRF) of Pesaran and Shin (1998), which accounts for covariance terms in Ω when tracing out the responses to a given shock. In addition, the ordering of the prices in y_t does not matter when using GIRF, unlike when using standard or orthogonalized impulse response forms.

Figure 8 traces out the response of base and peak electricity prices to a 1€-shock to EUA

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[15]The null hypothesis of Johansen's rank tests is that rank$(\alpha\beta') \leq r$. Thus, as is common practice, we conclude that the rank of $\alpha\beta'$ is the first r value where the test fails to reject the null hypothesis.

[16]It is possible that the results from the other markets pick up an input-price-only cointegrating relationship and no relationship with the electricity prices; however, looking at the parameters of the cointegrating vector, we find statistically significant parameters when normalizing on electricity prices. This suggests that the electricity prices are not being "zeroed-out" of the cointegrating vector.

prices at time zero, based on the individual-country VECM analyses. Similarly, Figures 9 and 10 contain the plots of base and peak electricity price responses to a shock in coal and natural gas prices, respectively.[17]

Figure 8: Responses to a EUA price shock
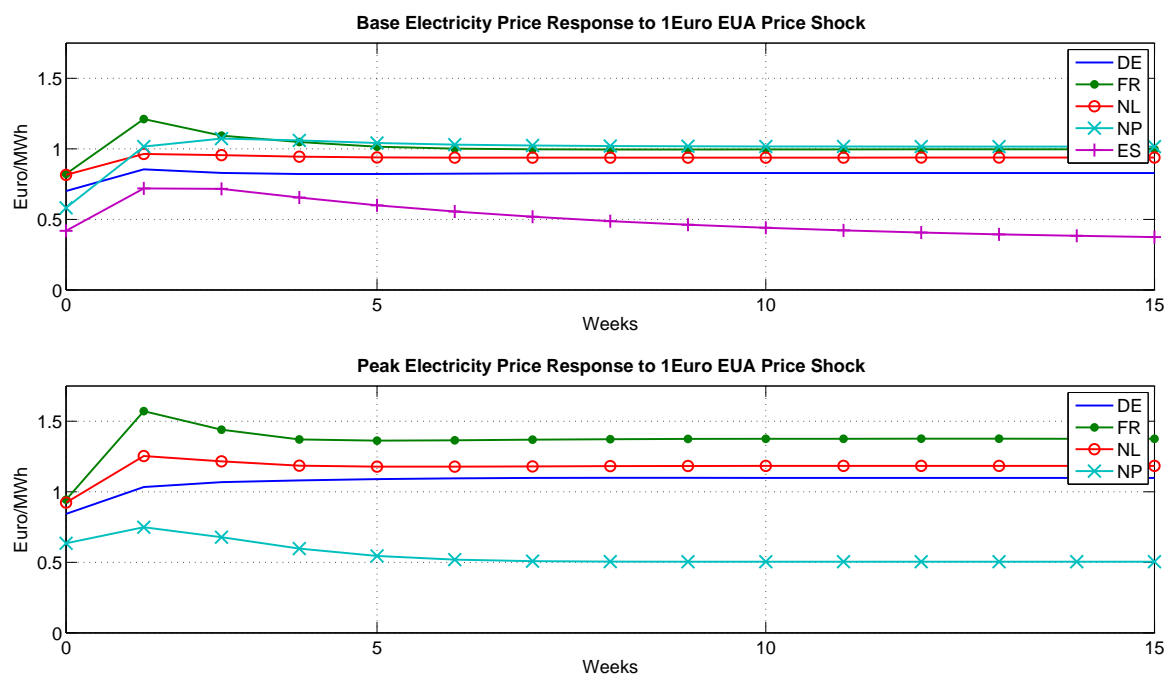
Baseload electricity price responses to a one-time EUA price shock stabilize at 0.4€/MWh for Spain, and around 0.9-1.1€/MWh for the other countries in our sample.[18] This is consistent with full pass-through of carbon costs associated with baseload generation assuming coal is mostly on the margin during base periods. The lower carbon content in Spain could be explained by the high share of gas generation in combination with transmission constraints to the continental markets.[19] Alternatively, if coal generation is the price-setting technology for base production in Spain, the lower estimated pass-through may be due to market power

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[17]The 95-percent confidence intervals in Figures 7-10 were calculated using the bootstrapping method described in Lütkepohl (2005). We excluded these confidence intervals from these figures for clarity's sake. In all cases, except the long-run responses of the FR electricity prices to coal price shocks, the derived responses, across all periods examined, were found to be statistically different from zero based on the 95-percent confidence intervals.

[18]In keeping with the tradition of the cointegration literature, we display the results in Figures 7-11 in the units of the dependent variable (this is the effect on the electricity price of a one-unit shock in one of the input prices), whereas the units in Figures 5-6 are those of the estimated coefficients. To move from the latter to the former, simply multiply the carbon price coefficient by 1 €/tCO$_2$, and the fuel price coefficients by 1 €/MWh fuel.

[19]With unconstrained transmission and thus fully integrated electricity markets, there would be only one marginal generator for the entire market. However, transmission constraints exist, and they are binding during a significant number of hours during the year. Furthermore, it should be noted that the results presented are similar to those obtained when modeling this country-market with a cointegrating rank of two.
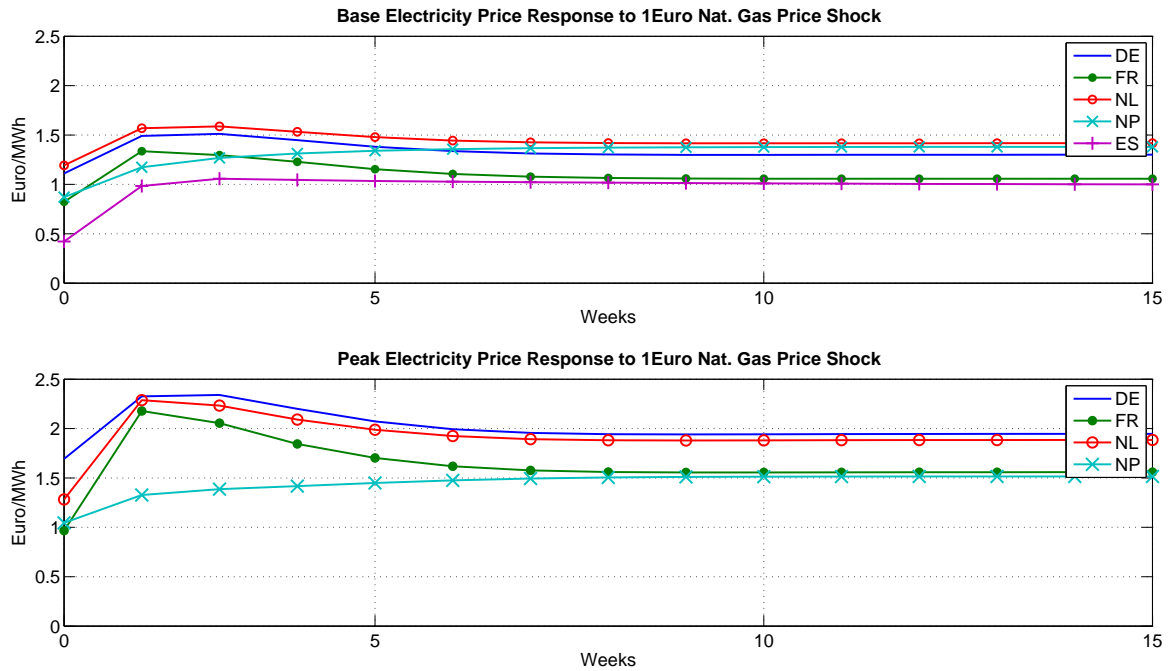
Figure 9: Responses to a coal price shock

Base Electricity Price Response to 1Euro Coal Price Shock

Peak Electricity Price Response to 1Euro Coal Price Shock
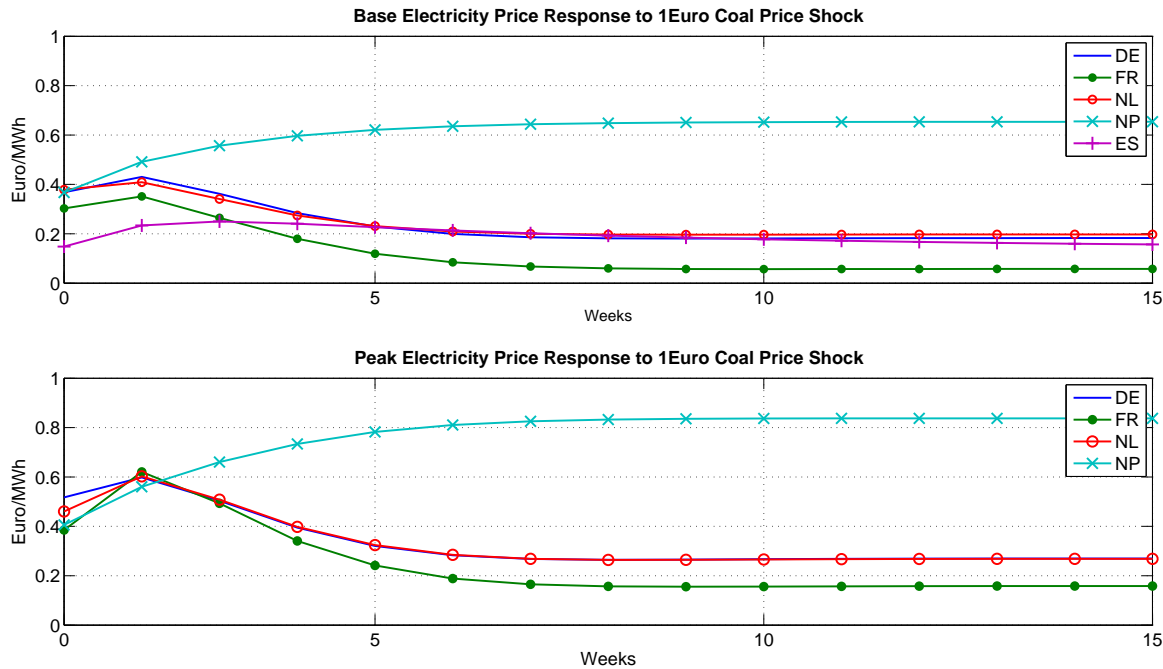
consistent with the extended theory model given in the Appendix.[20] Additionally, while one might expect Nordpool to have a lower pass-through rate in baseload due to the prevalence of hydro, coal-fired generation, which does exist to some extent in Nordpool, may still be on the margin during many offpeak hours in this market. Hydro generators in Nordpool may also price as the substitute for its power would price (i.e., hydro generators may price as coal generators would price), leading to high pass-through rates even if hydro was on the margin.

Peak price responses in the Nordic area are lower than baseload responses and are therefore consistent with a higher share of gas generation during peakload periods. This also corroborates the results obtained by Fell (2010) for this market. For Germany and the Netherlands, the electricity price response to a carbon price shock is slightly higher in peakload than in baseload, which is contrary to conventional wisdom but consistent with our results from the exogenous-price model, as well as with results reported by Zachmann and von Hirschhausen (2008).

Again, we find French peakload noticeably more responsive than baseload to a shock in

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[20]If market power were the main reason for Spain's lower pass-through rate, one might also expect to find similar results in other highly concentrated markets, such as in France, but we do not find this. In sum, our estimation frameworks are not suited to prove or disprove the existence of market power. We thus mention it as a possibility among other explanations.

Figure 10: Responses to a natural gas price shock

Base Electricity Price Response to 1Euro Nat. Gas Price Shock

Peak Electricity Price Response to 1Euro Nat. Gas Price Shock

carbon and coal prices, which is difficult to explain by marginal cost pricing, as is the fact that the Nordic response to coal is higher than for all other countries. However, we emphasize the caveat that these peak price responses are based on system estimators that have many complicated price feedbacks, and that they do not explicitly account for possibly relevant cross-country correlations. Furthermore,

Moving on to the electricity price responses to natural gas, we find some initial heterogeneity in the electricity price responses to a 1-€-shock in the natural gas price for both peak and base price series, but the longer-run responses are relatively similar across countries. The base-price response for a given country is generally lower than that for the corresponding peak-price response.

Overall, our single-country cointegration results are similar to the ARCH results; exhibiting larger peakload than baseload responses for DE, FR, and NL, but not for NP. Also, while not shown here, parameter estimates associated with many of the exogenous variables included in the estimations are as expected. More specifically, we find a negative effect for French reservoir levels on DE, NL, and FR base and peak prices, and a negative effect of NP reservoir levels on NP base and peak prices.

Table 3: Multi-Country Cointegration Rank Tests

Grouping:	Base DE,ES,FR,NP,NL	Peak DE,NP,NL,FR
$r = 0$	241.3**	220.4**
$r = 1$	166.8**	131.9**
$r = 2$	101.8**	75.6**
$r = 3$	66.8	42.1
$r = 4$	38.9	20.0
$r = 5$	21.9	9.7
$r = 6$	10.5	2.9
$r = 7$	4.9	-

Note: The null hypothesis is rank$(\alpha\beta') \leq r$. "**" and "*" denote rejection of the null hypothesis at the 5% and 10% significance levels, respectively.

5.3 Multi-Country Cointegration Analysis

To begin the multi-country analysis, we again conduct Johansen trace tests. This is conducted for the baseload price grouping, where all the available prices are included in y_t (i.e., $y_t = [P_t^{DE}, P_t^{ES}, P_t^{FR}, P_t^{NL}, P_t^{NP}, G_t, C_t, A_t]'$ for baseload), and for the peakload grouping, which is the same as that for baseload, with the exclusion of Spanish prices due to data availability. The results from the trace tests are given in Table 3. The table gives the "country groupings" in the header of each column, which denote the electricity price series included in the y_t vector along with the natural gas, coal, and EUA price series. Below these headers are the Johansen trace statistics.

For both the peak and base price groupings we find evidence of three cointegrating relationships among the electricity prices and input fuel prices and thus fewer than among the number of included electricity prices in the y_t vector. This suggests that beyond the possibility of short-run interactions among the markets, some markets may interact within a long-run relationship as well.

Applying the results of the cointegrating rank tests, we estimate the VECMs for the base and peak specifications and use these estimated parameters to form the impulse responses. The plots of the impulse responses are shown in Figure 11, with base price responses in the top panel of and peak-price responses in the bottom panel. In order to assess the statistical significance of the responses, we plot the long-run responses along with the corresponding

24

boot-strapped, 95-percent confidence intervals in Figure 12.[21]

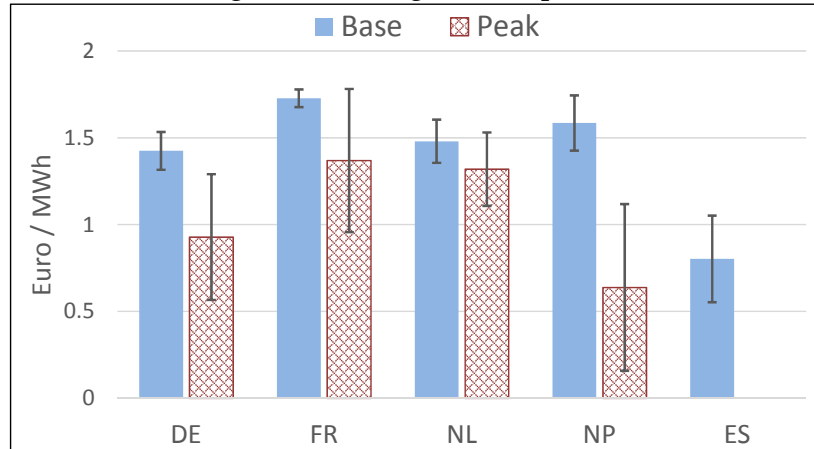Figure 11: Multi-Country Electricity Price Responses to EUA Price Shock
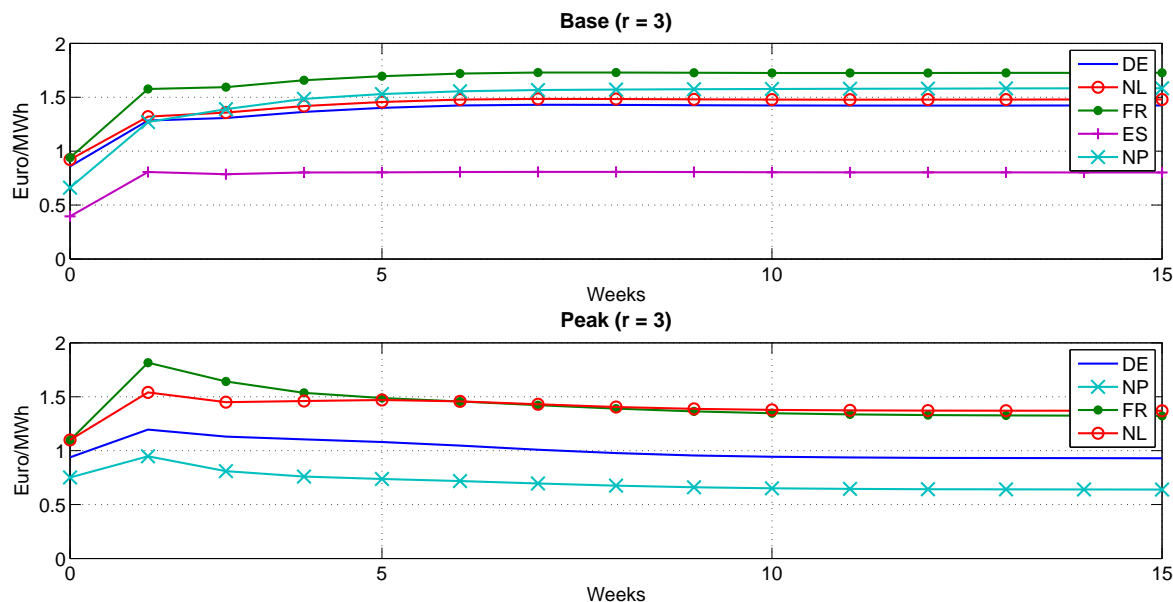
For the base price responses, we find all countries except Spain level off in the range of about 1.5–1.8€/MWh. These responses are higher than the corresponding responses from the individual analysis. The observation that the individual-country and multi-country results are different is not that surprising given that the multi-country analysis allows the markets to be related in many more ways than the individual-country analysis allows.

The base price response for Spain is considerably lower than for the other countries, with a response stabilizing near 0.8€/MWh. Again, we might expect a lower response for base prices in Spain given its relatively high percentage of natural gas-fired generation as shown in Figure 1, making natural gas plants more likely to be the price-setting technology across most hours, or the low response may be caused by a market power situation as the model given in the Appendix predicts.

Consistent with the ARCH model and individual-country cointegration results shown above, the peak price responses for the multi-country analysis start near or above where the base price responses begin, but then stabilize at lower levels than the corresponding baseload responses. This finding is more in line with the expectations that natural gas generators are

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[21]The long-run responses are the impulse response estimates, with 95-percent confidence intervals, at 15 periods after the initial EUA price shock. By this period, all responses have stabilized.

Figure 12: Long-run Responses

the price-setting generators during more of the peak hours, and, thus, the peakload response should be lower than that of the baseload. Also, we find that peak and base responses for DE and NP are statistically different from one another in the long run, but not for the other countries. Our multi-country cointegration results are therefore consistent with full cost pass-through based on marginal cost pricing, but the variance of our estimates does not allow for a more precise determination of the level of cost pass-through for most individual countries.

We also omitted parameter estimates from other exogenous variables included in the model, though again we found that FR reservoir levels negatively affected FR, DE, and NL electricity prices, NP reservoir levels negatively affected NP prices, and wind generation had a generally insignificant effect on the futures prices.

Finally, through the estimated VECM, we can also ascertain the effect of coal and natural gas price shocks on EUA prices, which is the subject of a different strand of literature.[22]. Because allowance price determination is not the primary focus of this paper, we placed these results in the Appendix.

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[22]For a review of this literature in the context of Phase II of the EU ETS, see Hintermann et al. (2014).

26

6 Discussion

We analyze the relationship between electricity and input prices, including the cost of CO_2 emissions for five European electricity markets, based on one-year futures and using three different approaches: a single-country exogenous-price framework, a single-country cointegration model with endogenous prices, and finally a multi-country cointegration framework. In this transition from simpler to more complex modeling, we face a tradeoff. On the one hand, the assumptions placed on the underlying data-generating processes are relaxed by allowing for price endogeneity and cross-market cointegration. On the other hand, the more complex models make it impossible to interpret any single coefficient, and we have to rely on long-term impulse-response functions that are the product of a series of complex interactions among all variables. These models are also sensitive to the selection of included countries and to exogenous shocks and regime shifts. In other words, we have to choose between simple models that tend to place excessively stringent assumptions on the data, and complex models that "let the data speak for themselves" and produce results that are difficult to interpret and less robust.

Our results from the exogenous-price framework suggest that base price responses to an EUA price increase are in line with expectations that coal is the marginal technology during most hours. However, this framework found the peakload-price responses to EUA price shocks to be higher than the baseload-price response, with the exception of the Nordpool market. This result does not adhere to expectations, as it is typically thought that natural-gas-fired generators are on the margin during a significant fraction of peak hours, and hence we would expect responses to be lower in the peak periods that given natural gas has a lower carbon content. A possible explanation of the high carbon content of peak prices could be that the influx of renewables has driven gas partially out of the market and increased the number of peakload hours during which coal is price-setting. However, this would only explain a narrowing of the gap in the carbon content between the load periods, but not its elimination or even reversal.

Also, it is important to remember that we use future prices in order to abstract from contemporaneous shocks to electricity demand and supply. Future electricity prices do not reflect actual marginal costs of generation, but traders' expectations of these marginal costs,

27

and these expectations may not be fully captured by fuel and allowance futures. This introduces a measurement error, which may or may not be classical, and which may therefore bias the results, although it is not clear why this would lead to the high pass-through rates during peak hours that we observe. To avoid such a an "expectations bias", we believe that the analysis of carbon cost-pass through based on spot market data using cointegration models could prove to be a fruitful topic for future research.

The results from the single-country cointegration framework are largely consistent with the exogenous-price framework. However, in the multi-country cointegration analysis, our results are somewhat more in line with expectations. We find that, when using a specification which includes all available peak or base electricity prices along with the input prices in the dependent-variable vector, peak-price responses to an EUA price shock in DE, FR, NL, and NP are, at least in the long run, lower, and sometimes significantly lower than their corresponding base price responses. However, the peak price responses in the short run appear to be as high as the base responses. In addition, the long-run baseload responses for all countries except ES are higher than expected if coal-fired generators are predominantly the marginal generator during many hours of the baseload. Also, our peak-load findings for FR, GER and NL are substantially above the response one would expect if natural gas-fired generators are predominantly the marginal generators during peakload hours.

The results for the Nordic area are most in line with expectations of coal and natural gas being on the margin during offpeak and peakload, respectively, and this result generally holds across all methodologies. Although there may be alternative interpretations, this may be a sign of imperfect integration within European electricity markets due to transmission constraints. Allowing for cross-market links that are not effective during many hours may introduce spurious cross-market relationships and bias the impact-response functions. Incorporating specific transmission constraints into the cointegration model could address this issue, but this would not only be econometrically challenging, but would also require information about the expected stringency of transmission constraints for each hour and some function to aggregate this information into weekly averages.

Methodologically speaking, our analysis shows that electricity and input prices are cointegrated within each electricity market in our sample, and that some of the electricity prices are

cointegrated across markets as well. Also, the results from our three estimation frameworks differ, which we can interpret as an indication that price endogeneity and market cointegration are sufficiently relevant to warrant the use of models that take these features into account. At the same time, the sensitivity of the results to the inclusion of other countries raises concerns about the robustness of these results, as does the imprecision of the estimates. Improved econometric techniques may be able to increase the quality of the estimates. For example, an estimation technique with endogenously determined time-varying parameters that adjust to changing marginal technology and general changing market conditions would allow for more dynamic pass-through estimations. However, no such model exists to date.

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Appendix

Derivation of eq. (3)

Totally differentiating (2) with respect to all its arguments leads to

$$dP = \left(\frac{\partial p}{\partial F} + \frac{\partial p}{\partial R} \frac{\partial R}{\partial F} \right) dF + \left(\frac{\partial p}{\partial A} + \frac{\partial p}{\partial R} \frac{\partial R}{\partial A} \right) dA + \frac{\partial p}{\partial R} \frac{\partial R}{\partial X} dX$$
$$+ \left(\frac{\partial p}{\partial F} \frac{\partial F}{\partial P} + \frac{\partial p}{\partial A} \frac{\partial A}{\partial P} + \frac{\partial p}{\partial R} \frac{\partial R}{\partial P} \right) dP \tag{A.1}$$

The first two terms describe the total marginal effect of a change in fuel prices and allowance prices on the electricity price (directly as well as indirectly via residual demand), the third term is the effect due to a shock in the exogenous vector X, and the last parenthesis describes the feedback effect of a change in electricity prices via fuel and allowance prices and via residual demand. The marginal change in the cost of producing electricity with a change in residual demand is the slope of the inverse supply function:

$$\frac{\partial p}{\partial R} = \frac{\partial K}{\partial R} + \frac{\partial \eta}{\partial R} \cdot F + \frac{\partial \psi}{\partial R} \cdot A \equiv p_R$$

The change in residual demand in response to the price is the slope of the ordinary demand function, which is equal to the inverse of the slope of the inverse demand function P_R:

$$\frac{\partial R}{\partial P} \equiv \frac{1}{P_R}$$

Focusing on the effect of an exogenous shock to the allowance price by setting $dF = dX = 0$ in (A.1), substituting $\partial p / \partial F = \eta$, $\partial p / \partial A = \psi$, the definitions for p_R and P_R, and rearranging yields (3).

Adding imperfect competition

If electricity prices exceed marginal costs due to imperfect competition, we have to add a markup $m(R)$, which depends on the residual demand for fossil-based electricity:

$$P = p(A, F; X) = K(R) + \eta(R)F + \psi(R)A + m(R) \tag{A.2}$$
$$\text{with } m(R) \geq 0, m' > 0$$

31

Totally differentiating, setting $dF = dX = 0$ and rearranging as above leads to

$$\frac{dP}{dA} = \frac{\psi + (p_R + m')\frac{\partial R}{\partial A}}{1 - \psi\frac{\partial A}{\partial P} - \eta\frac{\partial F}{\partial P} - \frac{p_R + m'}{P_R}} \qquad (A.3)$$

From $m' > 0$, $\partial R/\partial A < 0$ and $P_R < 0$ it follows that cost pass-through under imperfect competition is lower than under marginal cost pricing, because the dominant firm(s) absorbs a part of the cost increase by decreasing the markup.

Effect of fuel prices on the carbon price

Our cointegration model can be used to generate any impulse-response function involving the endogenous variables. Whereas we focus on the sensitivity of electricity to input prices, the response of EUA prices to fuel prices may be of interest for the empirical literature about carbon markets. The response of EUA prices to a shock in natural gas and coal prices is plotted in Figure 13. These responses are based on the multi-country, base-price estimation, since the base includes all hours of the day. Consistent with the findings presented in Subsection 5.2, Figure 13 shows that a positive coal price shock lowers the EUA price, whereas an increase in natural gas prices increases it. However, the 95-percent confidence intervals for the EUA response to natural gas prices is quite large and shows the response is not statistically different from zero.

Figure 13: EUA Price Response to Natural Gas and Coal Price Shocks
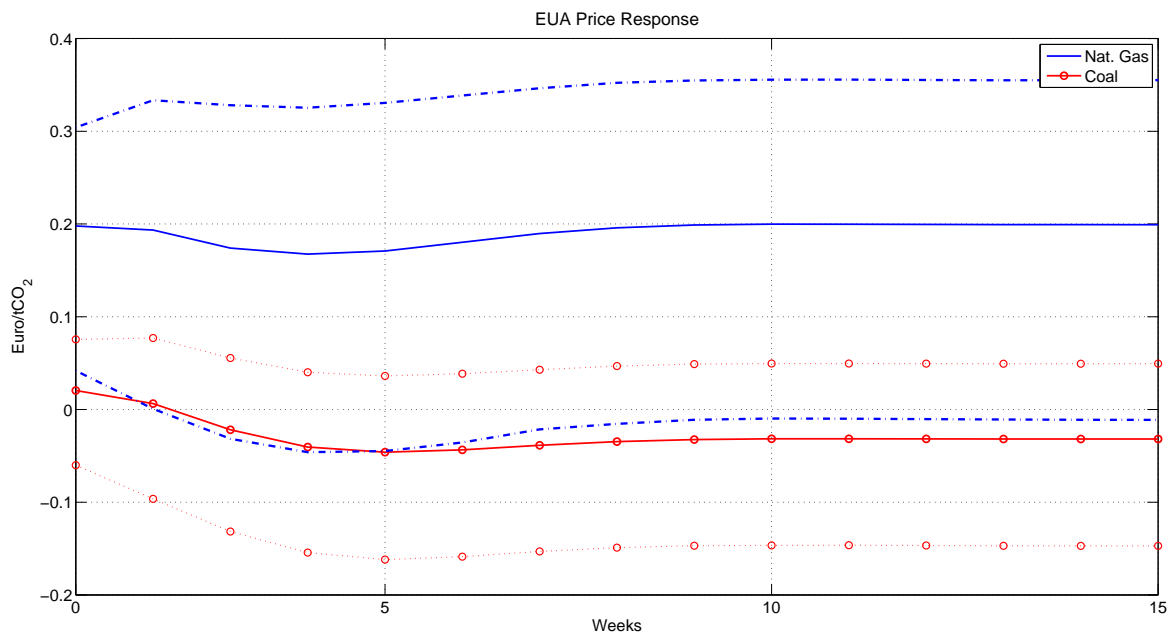
Note: The responses are based on the multi-country, base-price estimation. The solid lines represent the estimated responses and the 95-percent confidence intervals are given as dashed lines. For the response to a coal price shock, the estimated response and confidence intervals have a circle marker.