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Pass-through of CO_2 Emission Costs to Hourly Electricity Prices in Germany

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Abstract

I estimate the level of emissions cost pass-through to hourly wholesale electricity prices in Germany, based on spot market data. I control for contemporaneous shocks to demand and supply by constructing a detailed supply curve for fossil generation, and intersecting it with residual demand for fossil-based electricity for every hour. Determining the marginal generator allows me to use marginal fuel and carbon costs (rather than prices) as explanatory variables in order to identify the level of cost pass-through directly and with a high level of precision. I find that carbon costs are passed through to electricity prices by at least 84 %, with a central range of 98 %–104 % for different load periods. My results suggest that there is no economic reason for free allowance allocation to the electricity sector, and thus validate the updated allocation rules in Phase 3 of the European Union Emissions Trading Scheme.

JEL-Code: H230, H320, Q480, Q520, Q530, Q540.

Keywords: EU ETS, emission trading, air pollution, cost pass-through, electricity, climate change.

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1 Introduction

Emissions trading has emerged as one of the main policy instruments for slowing the speed of climate change, and it is arguably the most important application of market-based economics in an environmental context. Instead of forcing firms and households to behave in a particular way, cap-and-trade markets introduce a scarcity for a resource that was previously available in unlimited supply. Dividing the cap into small units and allowing firms to trade these allows an economy to reach the emissions cap at least cost, because emissions abatement takes place where it is cheapest. The European Union Emissions Trading Scheme (EU ETS) is the largest emissions trading system to date, with an emissions cap of around 2 billion tons of CO_2 per year that includes emissions from the most energy-intensive industrial sectors and accounts for around 40 % of the EU's total CO_2 emissions.

The fiscal impact of this type of climate legislation resides with the firms that have to surrender allowances to cover their emissions, net of any free allowances they receive from their governments and is thus straightforward to quantify, while assessing the incidence (i.e., the tax burden) is more complicated. Emission allowances are a necessary input for production that generates CO_2 emissions as a by-product, and we would therefore expect the EUA price to be reflected in product prices, just like the price of any other input. Because emission costs are opportunity costs, the pass-through of allowance costs should furthermore be independent of the method of allocation. A large share of the impact therefore resides with consumers and firms that purchase emission-intensive products. If the pass-through of (marginal) carbon costs to output prices is incomplete, a part of emissions costs may also be borne by the shareholders, workers and/or suppliers of the covered firms.

The market value of the aggregate emissions cap in the EU is currently around 10 billion euro per year; at its peak in early 2006 it was six times larger (corresponding to around 0.6 % of the EU's GDP), and because the cap is melted off in the future at an annual rate of 1.74%, the value is likely to increase again over time. From a public finance point of view, EU governments should secure this economic rent by selling all allowances and use the revenue to lower existing distortionary taxes, which is the same normative prescription that applies to corrective taxation (Bovenberg and Goulder, 1996; Parry, 1995). But this has not been done. Currently, about half of the allowances are given away for free, and during the first eight years of the system, almost the entire cap was allocated to firms free of charge. Therefore, the economic costs of the EU ETS are also borne by taxpayers that do not receive the full tax rebate, and due to the tax-interaction effect, the total burden is inefficiently high. Considering the size of the program, an appraisal of its efficiency and incidence is highly policy-relevant, also in the light of other emission permit markets that are being set up in other world regions.

There has been a lengthy policy debate about the merits of free allowance allocation to the industries included by the EU ETS, and a series of economic papers discuss this issue from various perspectives (Grubb and Neuhoff, 2006; Hepburn et al., 2006; Neuhoff et al., 2006). The "industry-friendly" argument claims that in order to avoid carbon leakage via a relocation of production activities to non-EU countries, and to maintain the international competitiveness of EU firms, the latter had to be allocated a significant share of emission allowances for free. This argument hinges on incomplete pass-through: If firms absorb a part of the carbon cost by lowering their profit margin, then (partial) free allocation may be justified due to carbon leakage and protectionist arguments. If, on the other hand, firms fully pass on their carbon costs to consumers, free allocation simply constitutes a transfer from taxpayers to firms without ancillary benefits in the form of protecting domestic jobs or avoiding leakage.

A series of papers have empirically estimated the degree of carbon cost pass-through to consumer prices, most of them focusing on electricity markets.[1] Sijm et al. (2006) report positive rates of cost pass-through using OLS regressions on electricity spreads for 2005, based on daily future prices, in the order of 60–117 % for Germany, and of 64–81 % for the Netherlands.[2] Sijm et al. (2008) extend this analysis in time and space and find positive but incomplete carbon cost pass-through for Germany, France, the Netherlands and Sweden, and (possibly) full pass-through for the United Kingdom. Other papers that have used either price or spread regressions include Chernyavs' ka and Gulli (2008) and Honkatukia et al. (2013). As I show in this paper, regressing electricity prices on input prices, rather than on marginal input costs, leads to biased estimates if the heat rate and the emission intensity

[1] An exception is the analysis by Smale et al. (2006) who focus on the other sectors included in the EU ETS and find pass-through rates that are typically lower than for the electricity market, and which depend on an industry's exposure to competition from outside the EU.

[2] Electricity spreads are the difference between the electricity price and the fuel cost, usually based on one standard fuel (coal for dark spreads and gas for spark spreads).

of the marginal generator are correlated with fuel and allowance prices. If the merit order is sensitive to prices, such a correlation would be expected. Furthermore, using electricity spreads rather than prices as the dependent variable introduces another source of bias if fuel costs are not passed through entirely, or fuels other than the one underlying the electricity spread are marginal during some hours.

A different strand of the literature has focused on the long-term relationship between electricity, fuel and carbon prices using cointegration frameworks, based on the concern that these prices may all be determined jointly, and that prices may react to shocks in a delayed manner (Fell, 2010; Fell et al., 2013; Fezzi and Bunn, 2010; Lo Prete and Norman, 2013; Zachmann and von Hirschhausen, 2008). Overall, these papers find that carbon costs are passed through to electricity prices in the sense that the prices for electricity, allowances and input fuels share a common trend. Due to the multitude of interaction effects in vector error-correction models, the effect of a change in an input price on the electricity price has to be computed using impulse-response functions, which tend to be sensitive to the inclusion of additional control variables or lags in the underlying model, and also to have large confidence intervals. Also, these models are typically run on data aggregated to the daily or even weekly level in order to reduce the noise and thus obtain reasonable long-term adjustments– an improvement which comes with a significant reduction in the degrees of freedom, and at a risk of an aggregation bias. Last, this part of the literature has focused on futures data. This makes the analysis independent of contemporaneous shocks to the demand and supply of electricity, but the downside is that in suppressing such shocks, models based on futures data lose a source of variation that is very useful in identifying the level of cost pass-through.

The paper that is most closely related to mine is by Fabra and Reguant (2014), who measure the pass-through of emissions costs in the Spanish electricity market. Whereas most of their regressions rely on input prices as explanatory variables, they also report estimates from a model that is based on marginal input costs for the five largest firms, for the hours during which these firms are price-setting. They find that carbon costs are passed through fully, but that fuel cost pass-through is incomplete.

In this paper, I estimate short-term cost pass-through using hourly spot market data from the German wholesale electricity market. By building a detailed dispatch model for electricity and including hourly information about stochastic electricity demand and supply, including data on renewable sources, I can identify the marginal generator and thus estimate the level of cost pass-through directly based on marginal input costs. Because I have marginal cost estimates for each hour, I can estimate cost pass-through for different load periods.

I find that carbon costs are passed through fully to wholesale electricity prices, with confidence intervals ranging from 89 % to 116 % for baseload and from 84 % to 114% for peakload, and the results for different load periods are qualitatively similar. This suggests that a free allocation of emissions permits is simply a gift to firms, as they are already reimbursed for their emissions costs by consumers. Fuel costs, on the other hand, appear not to be passed on completely with the possible exception of very low demand periods.

I further use my data to highlight problems arising when estimating cost pass-through based on prices. The level of cost pass-through can be inferred from price-based regressions only under strong assumptions. Because the estimates differ between the structural (i.e., marginal cost-based) and reduced-form (i.e., price-based) models, these assumptions do not appear to hold. I further show that aggregating the data to a daily or even weekly level not only increases the confidence intervals, but also affects the point estimates, indicating the presence of an aggregation bias.

The next section defines the concept of cost pass-through and introduces the empirical model. Section 3 discusses the market environment and presents the data, Section 4 shows the results, and Section 5 concludes.

2 Estimation of cost pass-through

In this section, I define cost pass-through in the electricity market and present the empirical model to estimate it.

2.1 Cost pass-through in electricity markets

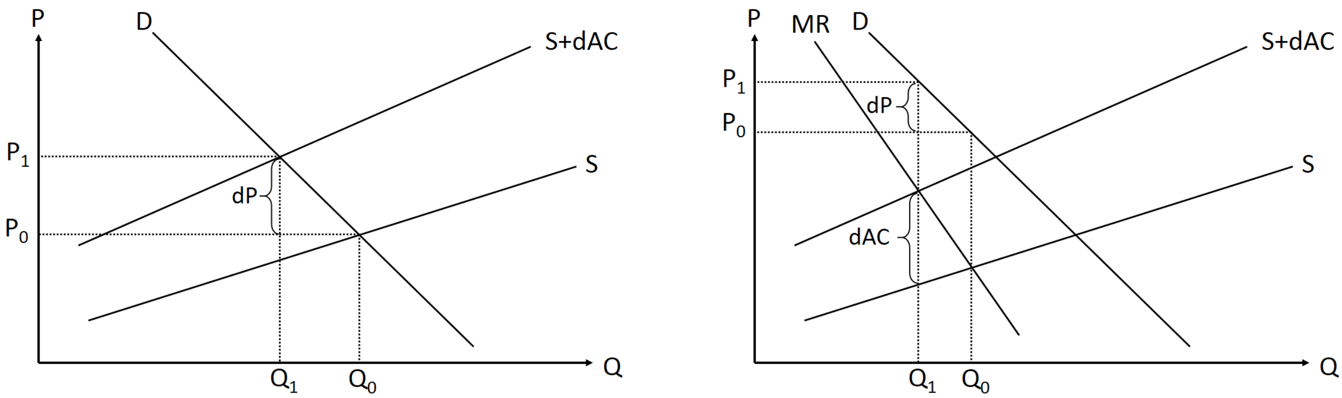
Let P refer to the electricity price, and MC refer to the marginal cost of producing another Megawatt hour (MWh) of electricity. Marginal costs of electric generation by fossil fuels are composed of fuel costs FC, allowance costs AC, and some other variable costs VC. The extent to which a change in any of these costs is transferred into a change in the electricity price depends on the degree of competition as well as on the price responsiveness of demand and supply.

Figure 1 illustrates the case of cost pass-through for linear demand and supply functions. The left-hand side panel shows the case under perfect competition. Suppose we start at an initial equilibrium given by (Q_0, P_0). If the allowance price A increases by dA, the marginal cost of generation increases by $dAC = dA \cdot \rho$, where ρ is the emission intensity of the marginal generator, and the supply curve shifts up by this amount (this shift will not be parallel if the emission intensity differs across different levels of output). Due to the demand response, the output price increases by $dP \leq dAC$. The rate of cost pass-through is given by

$$\frac{dP}{dAC} = -\frac{D_q}{D_q - S_q} \leq 1 \tag{1}$$

where D_q and S_q refer to the slope of the inverse demand and supply function, respectively. With inelastic demand or infinitely elastic supply, $dP/dAC = 1$, such that carbon costs are fully passed through to the electricity price. In general, cost pass-through in a perfectly competitive market increases with the elasticity of supply, and decreases with the elasticity of demand.

Figure 1: Cost pass-through under perfect (left) and imperfect (right) competition



Cost pass-through is lower if the output market is not competitive, because the monopolistic (or oligopolistic) firm absorbs a part of the cost increase by lowering its profit margin. With imperfect competition, firms set their marginal costs equal to marginal revenue, as illustrated in the right-hand side panel. The rate of cost pass-through is then given by

$$\frac{dP^M}{dAC} = -\frac{D_q}{MR_q - S_q} < -\frac{D_q}{D_q - S_q} \tag{2}$$

where the second inequality follows from the fact that the marginal revenue curve is always steeper than the inverse demand curve.[3]

Eqs. (1)-(2) imply that pass-through below unity can occur due to either a demand response, imperfect competition, or a combination of the two. However, short-term demand for electricity is most likely inelastic, because it is the sum of demand by retailers (who face a completely price-insensitive demand by consumers) and industry. Demand for wholesale electricity by the latter may be somewhat elastic, because plants can ramp production up and down (although this may entail a large opportunity cost), and because some firms can generate electricity onsite. Since I work with total demand and my generation portfolio includes industrial generators (see below), a shift of generation away from third-party producers to on-site industrial generation will not manifest itself as a demand decrease in my data.[4] Conditional on the assumption of no demand response being correct, incomplete pass-through of carbon costs would therefore be a sign of imperfect competition.[5]

Although this subsection has focused on an increase in marginal costs due to an increase in the price of CO_2 allowances, the same pass-through rates should apply to fuel and other variable costs. In principle, there is no reason why firms would treat different cost components differently, if their objective is the maximization of overall profits.

2.2 Empirical model

The core of my strategy for estimating the level of cost pass-through is a structural approach in the sense that I use fuel and carbon marginal costs as explanatory variables for the elec-

[3]More generally, cost pass-through is less than complete under imperfect competition if the curvature of the demand curve is sufficiently low. The curvature threshold at which cost-pass-through under monopoly is unity is somewhere between linear (incomplete pass-through) and iso-elastic (pass-through more than one).

[4]Fabra and Reguant (2014) use individual firm bids in the Spanish wholesale market to separately identify the change in markup and the demand response, and find the latter to be very small. Neither firms' individual bids in the day-ahead market, nor their forward positions (which are required to determine the actual demand and supply curves) are available in the German electricity market.

[5]Note that a finding of imperfect competition would not necessarily imply that firms should be allocated all their permits for free. As shown in Hintermann (2011), a sufficiently generous free allocation in the presence of imperfect competition introduces an incentive for firms to inflate the permit price, thus increasing the overall costs of climate regulation.

tricity price, which requires the determination of the marginal generator for every hour in my dataset. In a second step I compare my results to those obtained by a reduced-form approach that relies on fuel and carbon prices instead.

I use hourly residual demand for fossil-based electricity (simply "residual demand" hereafter), along with daily fuel and carbon prices, to identify the marginal generator for each hour. I compute residual demand as the sum of domestic demand, net exports and the energy used for pumped storage, net of all electricity from generators that have very low marginal costs and are therefore at the bottom of the generation merit order.[6] This includes generation from nuclear, hydro, solar, wind, biomass and waste incineration, as well as lignite, which is fossil, but which has a lower marginal cost than hard coal. Because consumer demand as well as some forms of must-run electricity (especially wind and solar) are stochastic, residual demand is stochastic as well and varies for each of the 8,760 hours of the year.

In my base specification, I regress the hourly electricity price, net of a generic variable cost that varies by technology, on hourly marginal fuel and allowance costs plus a constant, a trend, and a vector of dummies D_t:

$$P_t - VC_t = c_0 + c_1 t + \alpha_F FC_t + \alpha_A AC_t + D_t \Gamma + \epsilon_t \tag{3}$$

where ϵ_t is an error with expectation of zero and covariance matrix Ω. D_t includes dummies for each month-weekday-hour combination (i.e., 12 x 7 x 24 -1= 2,015 individual dummies) to account for the intra-weekly and seasonal price variation beyond what is explained by varying demand levels and input costs, and additional dummies that mark hours when residual demand is negative, and when industrial generators are marginal.[7] To allow for the possibility that the electricity price is determined differently during different hours of the week, I interact all variables in (3) with dummies for "generic" peakload hours, more finely defined dummies for periods with very high and very low demand, as well as dummies for every individual hour of the week (for a definition of these load periods, refer to Section 3).

[6]The merit order is the sequence according to which generators are brought online; in a liberalized market such as Germany, the merit order is based on least cost.

[7]Negative residual demand occurs in 2013 only, and often corresponds to negative electricity prices. During these hours, producers pay a price for not having to take their plant offline, which may involve costly ramping costs. I included the industrial generator dummy, because these generators are often not run based on least electricity costs, but on maximum overall profits (including the product market), which may not coincide.

Note that among these load curve differentiations, only peakload and baseload (average of all hours) are traded on forward markets.

I compute marginal fuel and allowance costs for every hour from January 2010 through November 2013 by intersecting the hourly residual demand with the generation portfolio for fossil-based electricity. These marginal costs (in EUR/MWh electricity) are defined by

$$FC_t = hr_t^m \cdot F_t^m \tag{4}$$

$$AC_t = hr_t^m \cdot ef_t^m \cdot A_t \tag{5}$$

where hr_t^m is the heat rate of the marginal generator in hour t (in MWh fuel / MWh electricity), F_t^m is the fuel cost of the marginal generator which is either the price of coal, natural gas or gasoil (in €/MWh fuel), ef_t^m is the emission factor of the marginal generator (in tCO_2/MWh fuel), and A_t is the allowance price (in €/tCO_2). Note that the variation in marginal fuel and allowance costs within a day is exclusively due to the hourly variation in residual demand (as input prices vary on a daily rather than hourly level), whereas the variation in marginal costs across days is based on the variation in both input prices and residual demand.

The underlying assumption behind specification (3) is that the identity of the marginal generator is exogenous to the electricity price, which is equivalent to stating that demand is insensitive to the price in the short run. If the identity of the marginal generator, and thus the heat rate, were jointly determined with the electricity price, the estimate for α_F and α_A would be biased.[8] Note that in the long run, demand is likely not completely inelastic, because both residential and industrial consumers can adjust their technology over time.

In a fully competitive market where the electricity price is equal to the marginal produc-

[8]To address the possibility of endogeneity, I estimated (3) also using an instrumental variable approach, where I use allowance and fuel prices to instrument for marginal allowance and fuel costs, similar to the approach in Fabra and Reguant (2014). Tests for over-identification do not reject the null hypothesis that the instruments are valid, but the IV estimates are associated with much larger standard errors than the OLS estimates, reflecting the tradeoff between asymptotic bias and efficiency often encountered in IV regressions. The loss of efficiency is due to the fact that marginal input costs vary hourly, whereas input prices vary on a daily level, such that the variation exploited for identification in the IV estimation is much smaller. Because separate tests for endogeneity did not reject the null hypotheses that marginal allowance and fuel costs can be treated as exogenous to the electricity price, I chose to estimate the level of cost pass-through using the OLS rather than the IV estimator. The endogeneity test is based on the difference between two Sargan-Hansen statistics: One for the equation where the suspected variable (either marginal allowance or fuel costs) is treated as endogenous and replaced by an instrument, and another for the equation where the variable is not instrumented.

tion cost for each hour, α_F and α_A are equal to (1), whereas in the presence of market power, the coefficients are equal to (2). The null hypotheses of complete pass-through for fuel and allowance costs are

$$H_0^F : \alpha_F = 1\,; \qquad\qquad H_1^F : \alpha_F \neq 1 \tag{6}$$

$$H_0^A : \alpha_A = 1\,; \qquad\qquad H_1^A : \alpha_A \neq 1 \tag{7}$$

With linear demand curves, marginal pass-through should never exceed unity, which would imply one-sided testing of (6)-(7). However, because I use an underlying market model that is a simplification of the actual market (e.g., it excludes the cost of ramping plants up and down or transmission constraints), and because firms' true opportunity costs for fuel may not be captured by fuel prices, the coefficient estimates could turn out to be larger than one as well. I therefore use two-sided hypothesis testing.

Because the composition of costs should not matter to firms, I formulate a third hypothesis of equal pass-through:

$$H_0^{FA} : \alpha_F = \alpha_A\,; \qquad\qquad H_1^{FA} : \alpha_F \neq \alpha_A \tag{8}$$

I then carry out two extensions. First, I re-estimate (3) after aggregating the data on a daily and a weekly level and adjusting the vector of dummies accordingly, because most of the literature about cost pass-through has used aggregated rather than hourly data. Aggregation may lead to a bias as discussed in Geweke (1978). On the other hand, since hourly data are quite noisy, aggregation typically leads to an improved model fit. A reduction in noise and a focus on longer time periods is attractive especially in the context of VECMs used, for example, by Fezzi and Bunn (2010), Fell (2010) and Fell et al. (2013), which focus on the long-term adjustment of prices.

Second, I estimate cost pass-through using a reduced-form equation based on fuel and allowance prices, rather than marginal costs, which is the natural approach if the identity of the marginal generator, and thus the marginal fuel and carbon costs, are not known, and which is presumably the reason why almost the entire cost pass-through literature has focused on prices. Specification (3) becomes

$$P_t - VC_t = c_0 + c_1 t + \beta_C Coal_t + \beta_G Gas_t + \beta_O Oil_t + \beta_A A_t + D_t \Gamma + \epsilon_t \tag{9}$$

where the included explanatory variables refer to the price for coal, natural gas, oil, and EUAs, respectively.

To derive the identifying restrictions required to derive the level of cost pass-through from the price coefficients, I compare this to the estimation based on marginal costs. Suppressing the constant, trend, time dummies and VC_t for convenience, specification (3) can be re-written as

$$\begin{aligned} P_t =& \alpha_F \cdot \left(hr_t^C Coal_t + hr_t^G Gas_t + hr_t^O Oil_t \right) \\ &+ \alpha_A \cdot \left(hr_t^C ef^C + hr_t^G ef^G + hr_t^O ef^O \right) A_t + u_t \end{aligned} \tag{10}$$

The terms in parenthesis reflect marginal fuel and carbon costs and correspond to an expanded version of the definitions given in (4)-(5). The vectors of fuel-specific heat rates hr^i, $i = C, G, O$, contain the heat rate of the marginal generator if fuel type i is marginal in hour t, and zero otherwise. To arrive at the marginal carbon intensity, the fuel-specific marginal heat rates are multiplied by the heat rate of the corresponding fuel ef^i, which is a physical constant.

If the heat rate of the marginal generator is independent of input prices, it can be replaced by its mean.[9] Let $\bar{hr}^i = \sum_T hr_t^i / T$ refer to the unconditional mean of the fuel-specific heat rate, and $\bar{hr}_m^i = \sum_T hr_t^i / T_i$ refer to the average heat rate conditional on fuel i being on the margin, with T_i being the number of hours during which fuel i is price-setting. With independent heat rates, OLS on fuel and allowance prices yields unbiased estimates that correspond to

$$\hat{\beta}_i = \hat{\alpha}_F \cdot \bar{hr}^i = \hat{\alpha}_F \cdot \bar{hr}_m^i \cdot (T_i / T) \tag{11}$$

$$\hat{\beta}_A = \hat{\alpha}_A \cdot \sum_i \bar{hr}_m^i \cdot ef^i \cdot (T_i / T) \qquad \text{for} \quad i = C, G, O \tag{12}$$

[9]To see this, suppose we regress a vector Y on a vector $X \equiv W \odot Z$, where "$\odot$" is the pointwise multiplication operator. If W and Z are independent, it follows that $E[W \odot Z] = E[W] \cdot E[Z]$, such that we can regress Y on $\tilde{X} \equiv E[W] \cdot Z$.

Identification is achieved by adding the restriction that the marginal generation shares T_i/T have to sum to one. Solving (11) for the marginal generation shares and substituting into the identifying restriction and (12) leads to the following hypotheses of complete and equal cost pass-through:

$$\tilde{H}_0^F: \quad \alpha_F = \sum_i \frac{\beta_i}{\bar{hr}_m^i} = 1\,; \qquad \tilde{H}_1^F: \alpha_F \neq 1 \tag{13}$$

$$\tilde{H}_0^A: \quad \alpha_A = \beta_A \cdot \frac{\sum_i \beta_i / \bar{hr}_m^i}{\sum_i \beta_i \cdot ef^i} = 1\,; \qquad \tilde{H}_1^A: \alpha_A \neq 1 \tag{14}$$

$$\tilde{H}_0^{FA}: \quad \alpha_F = \alpha_A\,; \qquad \tilde{H}_1^{FA}: \alpha_F \neq \alpha_A \tag{15}$$

A rejection of the null hypotheses (13)-(15) is consistent with incomplete pass-through, but also with a violation of the underlying assumptions. If the heat rate of the marginal generator is not independent of input prices, we cannot substitute its mean. This not only changes the relationship between the $\beta's$ and the $\alpha's$, but OLS on (10) yields biased estimates, because input prices are correlated with the error term (see Appendix). Since the merit order depends on fuel prices, and the heat rate depends on the merit order, the independence assumption most likely does not hold.[10] Whether this is quantitatively relevant is an empirical question, which I address by comparing the estimates for cost pass-through based on prices with those based on marginal costs.

Lastly, some of the empirical literature has worked with fuel spreads rather than electricity prices (e.g., Sijm et al., 2008) and has regressed these spreads on allowance prices (but not on fuel prices), which requires an assumption about a particular technology being on the margin in a given load period, as well as an average heat rate for that technology. For example, to compute the dark spread, coal is assumed to be the marginal technology during all offpeak hours, with an average heat rate of 2.63 (corresponding to an efficiency of 38 %). Comparing such a regression to (9)-(10) and making the independence assumption leads to the following interpretation of the allowance price coefficient and the error term:

[10]Note that the independence assumption is between fuel prices and the *unconditional* heat rate, which is zero whenever the corresponding technology is not on the margin. The independence assumption therefore implies that the identity of the marginal generator has to be independent of fuel prices, which is unlikely to be the case.

$$P_t - \hat{hr}^C \cdot Coal_t = \beta_A \cdot A_t + \epsilon_t \tag{16}$$

$$\beta_A = \alpha_A \sum_{i=C,G,O} \bar{hr}^i_m ef^i \cdot (T_i/T) \tag{17}$$

$$\epsilon_t = (\alpha_F \bar{hr}^C - \hat{hr}^C)Coal_t + \alpha_F\big(\bar{hr}^G Gas_t + \bar{hr}^O Oil_t\big) + u_t \tag{18}$$

An unbiased estimate for β_A requires that $E[A_t \cdot \epsilon_t] = 0$. Because fuel and allowance prices are related,[11] the error term (18) implies that the estimate for β_A is unbiased only if $\alpha_F \bar{hr}^C = \hat{hr}^C$, and if $\bar{hr}^G = \bar{hr}^O = 0$. Intuitively, this is the case if fuel cost pass-through is complete ($\alpha_F = 1$), the heat rate assumed for the spread regression corresponds to the actual unconditional heat rate $\bar{hr}^C$, and no other fuel is marginal during the chosen load period. If these conditions hold, the hypothesis of full pass-through becomes

$$\hat{H}^A_0: \quad \alpha_A = \frac{\beta_A}{\hat{hr}^C_m \cdot ef^C} = 1 \qquad\qquad \hat{H}^A_1: \quad \alpha_A \neq 1 \tag{19}$$

In contrast, if these assumptions do not hold, and/or if the independence assumption fails to hold, the coefficient estimate on allowance prices will be biased.

3 Market environment and data

In this section, I briefly describe the German electricity market, present the data, and describe the construction of the dispatch model.

3.1 The German electricity market

The German electricity market was liberalized in 2005 in the context of EU-wide energy market reforms. Transmission remains a regulated natural monopoly, but the remainder of the wholesale market is competitive. Electricity producers sell power in forward markets to retailers and large industrial consumers. The European Energy Exchange (EEX) offers

[11]There is a sizeable literature about the determinants of the allowance price, and fuel prices have been identified as some of the main drivers (see, e.g., Aatola et al., 2013; Alberola et al., 2008; Hintermann, 2010; Mansanet-Bataller et al., 2007; Rickels et al., 2014).

standardized futures contracts that are settled financially for maturities of up to 6 years. Contracts are available separately for baseload (all hours) and peakload (8 a.m. to 8 p.m. on workdays) and are specified in terms of MW per relevant load period.[12] Electricity futures are settled financially, based on the difference between the futures price and the spot price that materializes throughout the delivery period.

In addition to the forward market, two near-term markets exist. The first is the day-ahead auction where market participants make demand and supply bids for each hour of the following day. These bids are aggregated into market demand and supply curves, and the market-clearing price for every hour is established. Day-ahead trading for German electricity takes place on the Elspot platform, which is a merger between Powernext (a French exchange) and EEX. Since 2008, a market for same-day delivery also exists. In order to ensure that demand equals supply at each moment in time, the transmission systems operator (TSO) is responsible for real-time balancing and thus has the ability to bring individual generators on- and offline, but this balancing is not market-based.

In theory , the last market sets the efficient price, whereas prior markets serve for hedging purposes and their prices may therefore not be equal to marginal costs. But because the intraday market is much less liquid than the day ahead auction, the day-ahead price for German electricity rather than the intra-day price is usually interpreted as the reference spot price most closely associated with marginal costs. I therefore use the hourly day-ahead price as my dependent variable.

3.2 Data

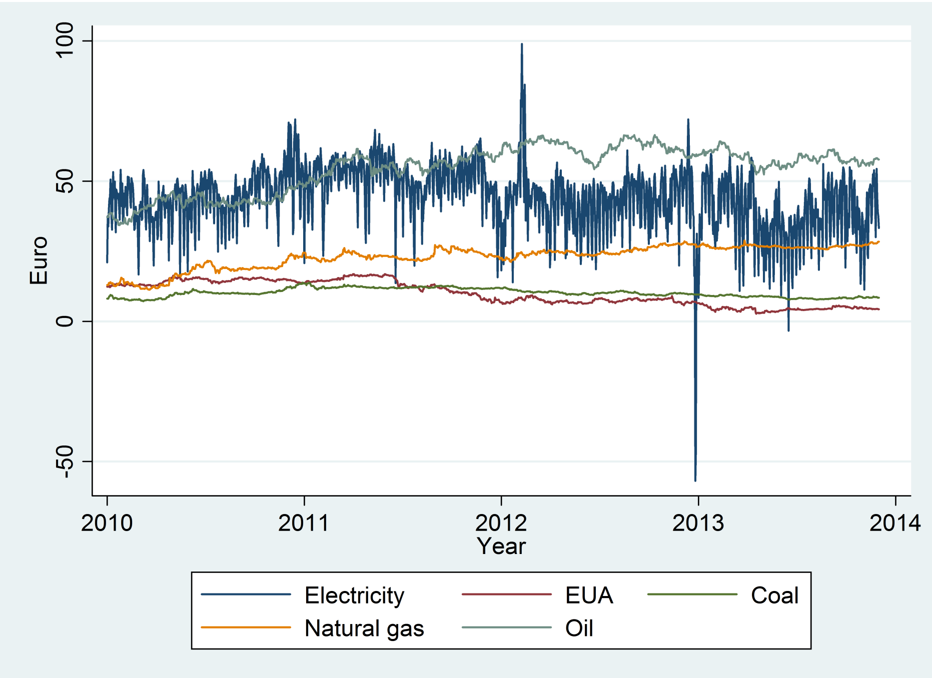
I use hourly electricity prices from Elspot (in €/MWh), accessed via Thomson Reuters (TR) Eikon. I further use the EUA spot price (in €/tCO_2), the next-month CIF ARA coal price, the EGIX natural gas price index for Germany, and the price for FOB ARA gasoil with a sulphur content of 0.2%,[13] all of which are measured with a daily frequency. These commodities

[12]For example, the seller of a one-year futures contract for baseload promises to supply one MW of electricity for each of the 8,760 hours of the next calendar year at the specified price.

[13]CIF stands for cost, insurance and freight and means that the price is inclusive of these costs; in contrast, FOB is an acronym for free on board and indicates that shipment and insurance have to be paid by the buyer. ARA stands for entry into Europe at the ports of Amsterdam, Rotterdam or Antwerp. The EEX CIF ARA coal future is based on the API(2) index, which is based on all coal entering north-western Europe by ocean freight. EGIX stands for European Gas index and is computed by EEX for both natural gas regions of Germany as well as a virtual, unified market.

are traded on EEX and accessed via TR Datastream. I converted all fuel prices into units of €/MWh of fuel. In order to match up the electricity prices from the day-ahead market with the (same-day) fuel and carbon prices, I shifted the electricity price data forward by one day such that trading and delivery dates coincide. Figure 2 shows daily input prices and the daily average of the electricity price.

Figure 2: Daily prices for German electricity, fuels and EUAs



To determine residual demand for fossil-based electricity, I start with total hourly demand for domestic generation, which is the sum of hourly consumer demand (including demand from industrial users), electricity use for hydro storage, and hourly net exports to other countries, all of which are available from ENTSO-E.[14] Because the coverage of hourly consumption monitoring is not quite complete, and pump use is only available on the monthly level, I had to make some adjustments to the demand data (for more details, see Appendix).

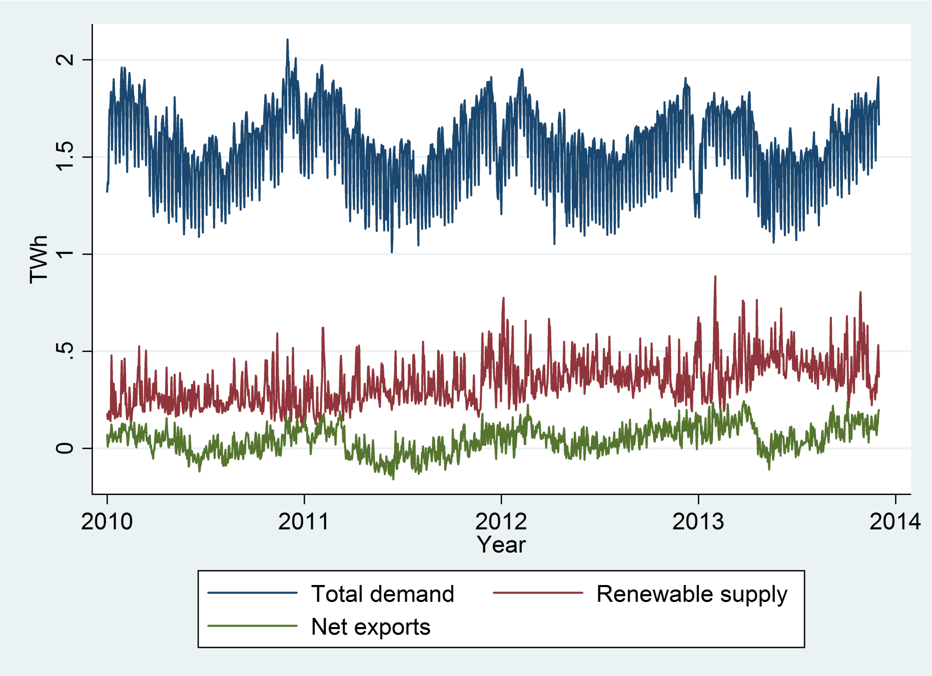
From this total hourly demand, I subtract generation from sources that have low marginal costs and can therefore be assumed to run whenever circumstances allow, which may be determined by environmental factors or planned outages. These "must-run" technologies include lignite, nuclear, renewables (wind, solar, hydro and biomass) and waste incineration.[15]

[14] European Network of Transmission System Operators for Electricity, available at https://www.entsoe.eu/.

[15] Although lignite generation clearly has positive marginal fuel costs, lignite-based generators typically run through continuously due to the very high startup and ramping costs; in fact, lignite generation in Germany is less variable than nuclear generation, as shown in Fig. 6 below. Also, since generation by biomass is typically associated with feed-in tariffs, I consider biomass as inframarginal, although the true marginal production costs may be considerable.

Hourly production by technology, with the exception of biomass and waste, is provided by the EEX Transparency platform, and I accessed historical series via TR Point Connect. For generation by biomass and waste incineration, I used monthly data from the German Federal Environment Agency and divided them among individual hours.[16]

Figure 3: Total demand, generation of renewables and net exports

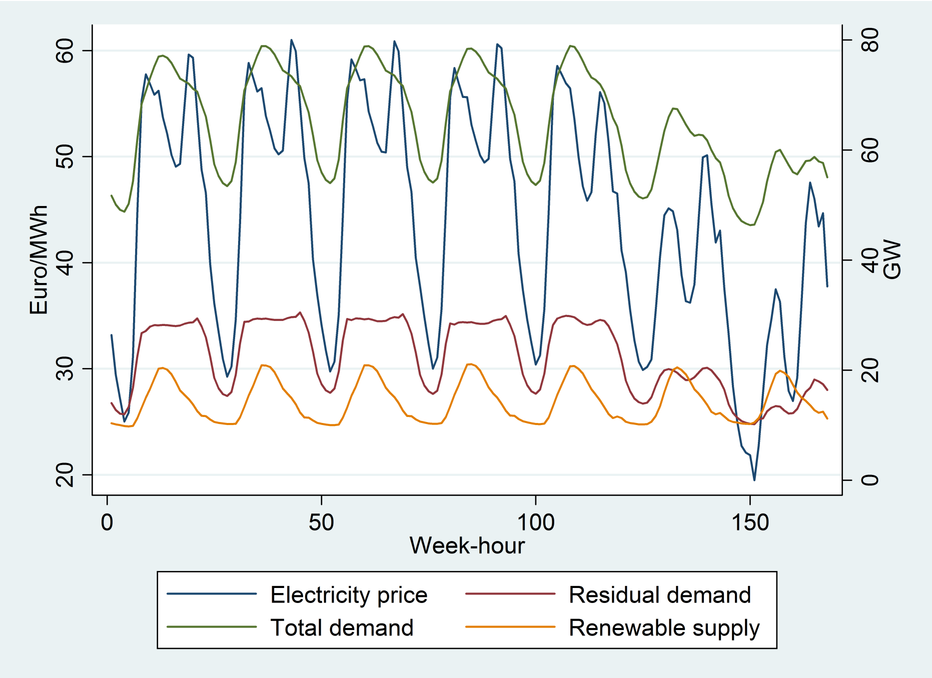


The variation in daily electricity prices in Figure 2 far exceeds the variation in input prices, and the hourly price variation is even greater, ranging between EUR –222 /MWh to EUR 210/MWh. This variation mainly comes from fluctuations in total demand and the supply of "free" electricity via the generation of renewables, as shown in Figure 3. Another, smaller source of variation are net exports to all neighboring countries.

Besides significant variation over time, electricity prices and residual demand also exhibit a pronounced intra-weekly variation. Figure 4 shows the average price for each hour of the week (starting with the hour from midnight to 1 a.m. on Monday), along with residual and total demand. The latter is also known as the load curve, because it reflects the total electric load in the grid per hour. The daily demand peaks roughly coincide with the price variation, although the former are unimodal, whereas the latter have two distinct maxima per day. The figure also shows that the influx of renewables occurs mainly during the day, with the effect of flattening the daily residual demand curve. Looking closely at the latter reveals the bimodal

[16]Publication titled "Erneuerbare Energien in Zahlen", available at http://www.umweltbundesamt.de/themen/klima-energie, last accessed in Feb. 2014.

Figure 4: Intra-week variation of prices, demand and supply by renewables



daily distribution that is amplified in the hourly electricity prices.

3.3 Identifying the marginal generator for each hour

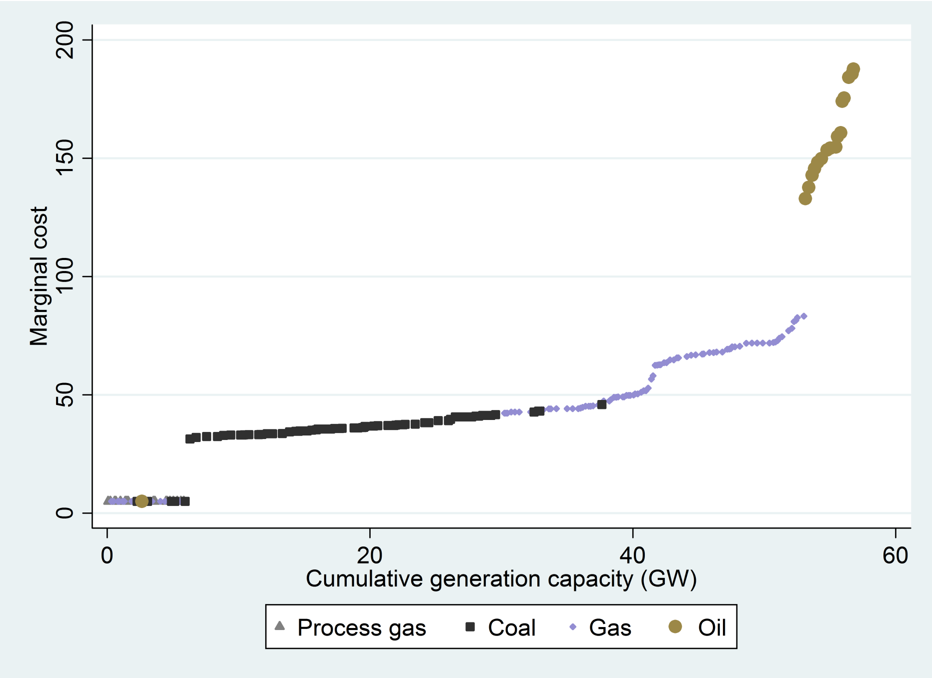
To construct the merit order, I use a generation portfolio provided by the German Federal Environment Agency, which contains information about all generators with an installed capacity of at least 100 MW.[17] The information available includes the type of fuel, the technology (i.e., combined-cycle or conventional), the year of construction and any major update or retrofit, and whether the generator is optimized for electricity output, heat, or industrial generation. The efficiency of each generator, however, is not given, and I therefore compute this based on the plant age and technology type. To compute the CO_2 intensity, I use fuel-specific emission factors from IPCC (2006). To this dataset, I merge generation information provided by the Bundesnetzagentur, which contains generators with an installed capacity greater than 10 MW, but no detailed information about the employed technology.[18] For more details underlying the construction of the generation portfolio, please refer to the Appendix.

I then compute the marginal fuel cost of each generator by multiplying the heat rate

[17] http://www.umweltbundesamt.de/daten/energiebereitstellung-verbrauch/kraftwerke, last accessed in January 2014.

[18] Available at www.bundesnetzagentur.de under the entry Unternehmen/Institutionen-Versorgungssicherheit-Erzeugungskapazitaeten-Kraftwerkliste, last accessed in January 2014.

Figure 5: Fossil-based merit order for average input prices

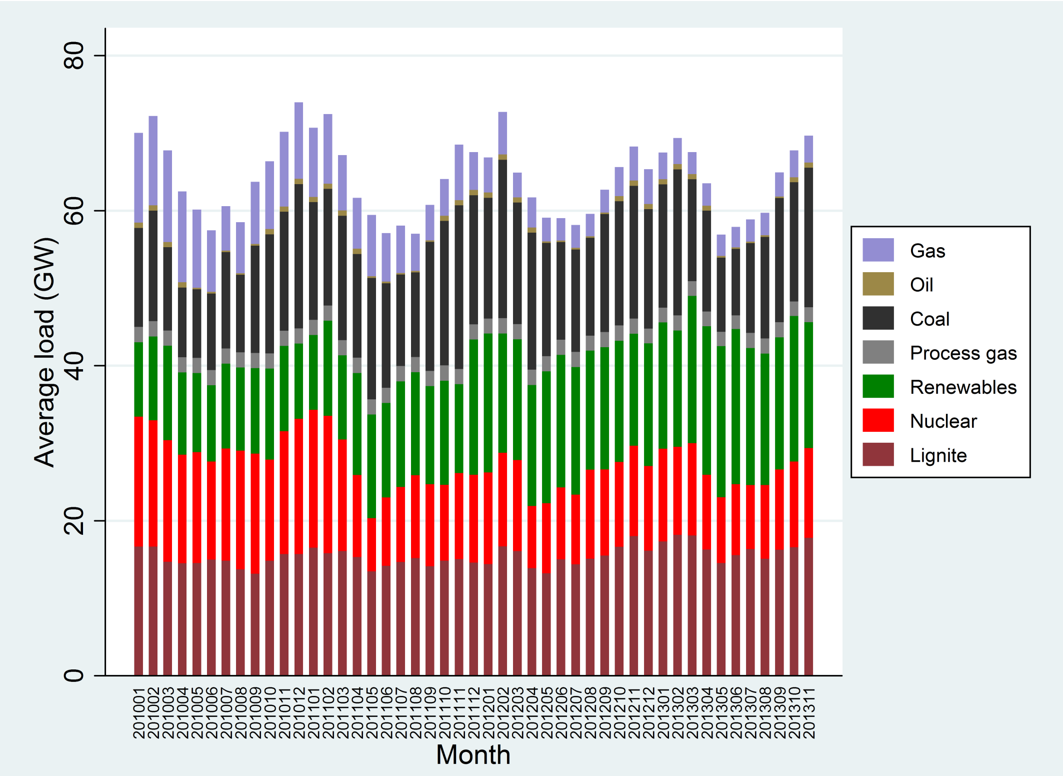


(defined as the inverse of the efficiency) with the fuel price, and the marginal carbon cost by multiplying the heat rate by the emission intensity and the allowance price. Since fuel and allowance prices have a daily frequency (workdays only), the marginal fuel and carbon cost per generator is constant within a day. For week-ends and holidays, I use the last available closing prices. Finally, I identify the marginal generator by sorting the generation portfolio by total marginal costs (i.e., the sum of fuel, carbon and other variable cost) and intersecting it with the hourly residual demand.

The resulting merit order for coal, gas, oil and process gas generation, computed based on average prices for coal, gas, oil and allowance prices, is shown in Figure 5. Because I assign industrial plants a very low marginal cost to reflect the fact that these are operated based on production needs rather than profit maximization on the electricity market, these plants appear at the bottom of the merit order. All generators based on process gas are included in this category, along with some coal, oil and gas generators.[19] Coal generation is on average cheaper than generation by gas, but some conventional gas plants are less efficient than the more efficient coal plants, such that there is some overlap in the merit order with respect to coal and gas generation. The most expensive plants are oil plants, and based on their

[19]Perhaps a more natural way of including industrial generation would be to subtract it from total demand along with other must-run technologies. However, because these plants typically do not have large startup costs, they may be taken offline more easily than lignite or nuclear plants, and thus serve as the quasi-marginal technology during hours of very low residual demand.

Figure 6: Generation by energy source by month



marginal cost of generation, they would practically never be used. However, many oil plants are deployed with a primary focus on heating rather than electric output. For the heating months (October through April), I therefore assign these plants zero marginal costs, such that some of the oil generation drops to the bottom of the merit order.

The share of generation by energy source based on my merit order model, including the must-run technologies, is shown in Figure 6. The generation portfolio that is relevant for residual demand generates about a third of the total electricity, whereas the other two thirds are from to nuclear, lignite and renewable generation. The figure also shows that generation by renewables has increased over time, driving out fossil-based generation in the process (mostly gas), but also replacing some of the nuclear power, the output of which was discretely reduced after the accident at the Fukushima nuclear plant in March 2011.

4 Results

I first present the results from the structural estimation before moving on to those based on the price-based approach.

4.1 Estimation of pass-through based on marginal costs

I estimate (3) by OLS separately for baseload, offpeak, and peak. The residuals exhibit autocorrelation that cannot be removed by adding lagged dependent variables, which is the reason why I omitted such lags.[20] To account for this autocorrelation, I use robust standard errors based on the Newey-West estimator, with an automatic lag order selection procedure derived by Newey and West (1994) and implemented by Baum et al. (2010). For the hourly regressions based on marginal costs, this resulted in a lag order of 74.[21]

Table 1: Results from estimating the marginal cost-model

	Hourly data, generic			Daily data			Weekly data			Hourly data, custom[c]		
	Base	Offp.	Peak	Base	Offp.	Peak	Base	Offp.	Peak	Med.	Low	High
Variables												
Fuel cost	0.898	0.904	0.893	1.019	0.999	0.987	0.981	0.953	1.024	0.894	0.944	0.897
st.dev[a]	0.053	0.062	0.052	0.087	0.077	0.098	0.090	0.109	0.103	0.049	0.102	0.044
p (α_F=1)	0.053	0.121	0.040	0.828	0.993	0.895	0.837	0.665	0.816	0.032	0.581	0.020
Carbon cost	1.024	1.038	0.989	1.125	1.176	1.091	1.008	1.201	0.976	0.980	1.065	1.031
st.dev[a]	0.069	0.083	0.074	0.221	0.206	0.196	0.283	0.280	0.283	0.064	0.115	0.076
p (α_A = 1)	0.723	0.649	0.877	0.573	0.392	0.644	0.976	0.583	0.933	0.759	0.571	0.686
p (α_F = α_A)	0.018	0.007	0.218	0.684	0.463	0.632	0.937	0.579	0.880	0.156	0.029	0.067
Dummies												
Month-wday-hr	(incl.)	(incl.)	(incl.)							(incl.)	(incl.)	(incl.)
Month-wday				(incl.)	(incl.)	(incl.)						
Month							(incl.)	(incl.)	(incl.)			
Special regime[b]	(incl.)	(incl.)	(incl.)	(incl.)	(incl.)	(incl.)	(incl.)	(incl.)	(incl.)	(incl.)	(incl.)	(incl.)
N	34'320	34'320	34'320	1'430	1'430	1'020	205	205	205	34'320	34'320	34'320
Deg. of freedom	32'299	32'294	32'294	1'341	1'341	955	188	188	188	32'289	32'289	32'289

a: Standard errors computed with the Newey-West estimator; b: dummy equal to one for hours with negative residual demand and for hours where industrial generation is marginal, and zero otherwise; this dummy is aggregated to a continuous variable (i.e., the share) for the daily and weekly regressions; c: Low between 11 p.m. and 5 a.m.; high between 10 a.m. and 4 p.m. on workdays; medium refers to all other hours.

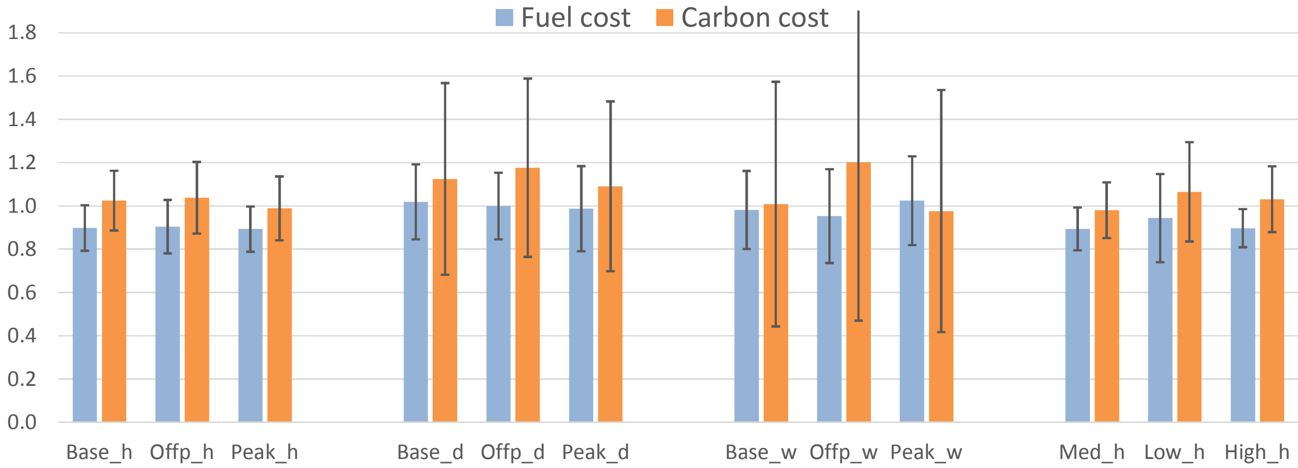
Table 1 shows the coefficient estimates and the test results for hypotheses (6)-(8) for various levels of aggregation, and for different load periods, and Figure 7 visualizes the results, with the error bars representing 95 %-confidence intervals. Beginning with the hourly results for baseload, offpeak and peak hours shown in the leftmost panel, the estimates imply that the pass-through of carbon costs is complete. The results for fuel costs are less clear. Whereas we cannot reject full pass-through for offpeak hours, we reject it at p=0.053 for

[20]With lagged dependent variables and an autocorrelated error, the coefficient estimate of the lagged dependent variables would be biased. Because this coefficient is required to estimate equilibrium pass-through, I excluded all lagged dependent variables.

[21]The resulting lag order differed for the price and spread regressions, and for the regressions aggregated to the daily and the weekly level.

baseload, and at $p<0.05$ for peakload. Lastly, the null hypothesis of equal pass-through of fuel and carbon costs is rejected for offpeak and baseload, but not for peakload.

Figure 7: Marginal pass-through of fuel and carbon costs

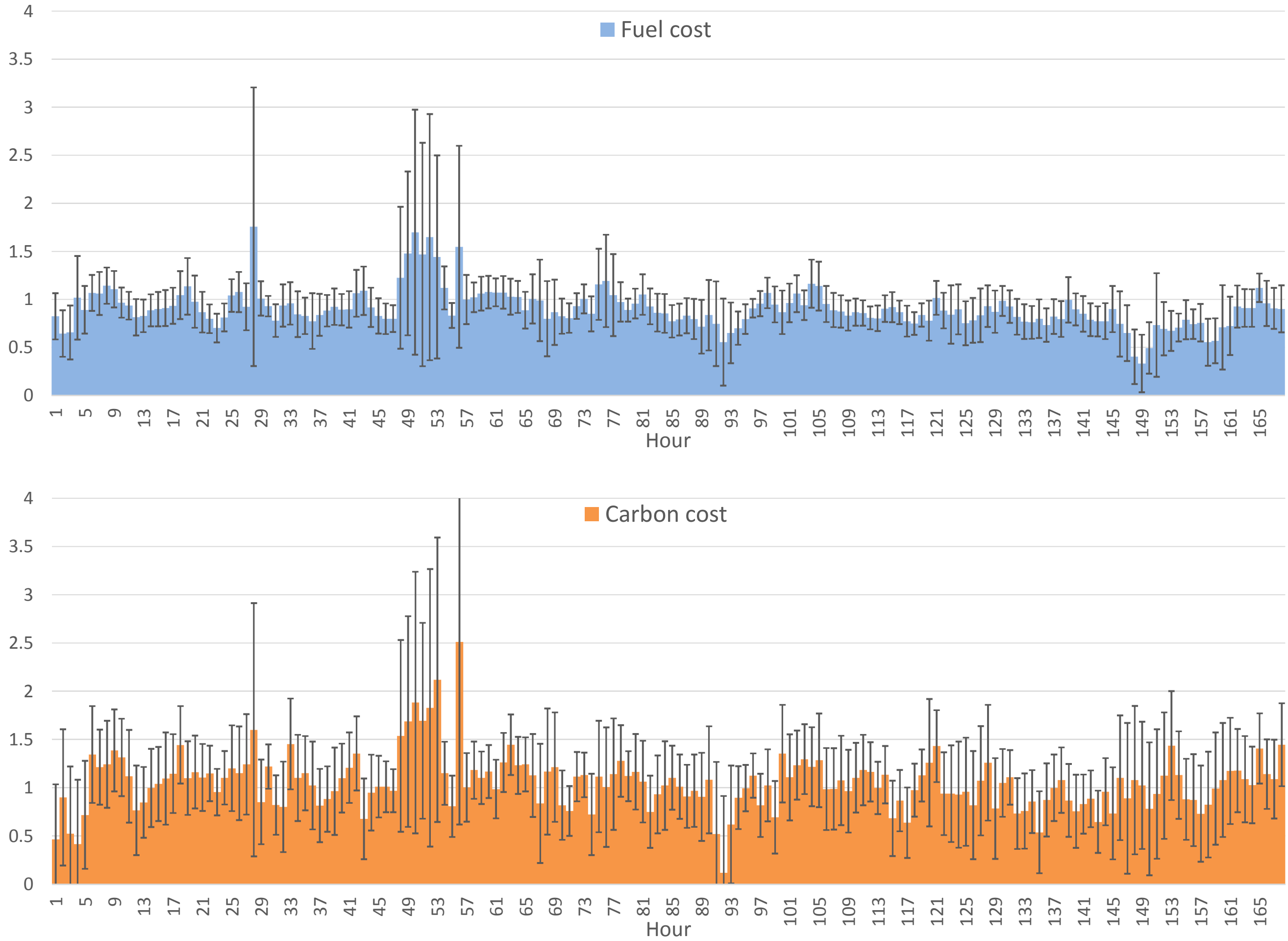


Note: The subscripts h, d an w refer to hourly, daily and weekly aggregation of the data, respectively.

Comparing the first three panels in Table 1, we see that data aggregation not only increases the confidence intervals and thus greatly reduces the power of the test (the null hypothesis cannot be rejected by a wide margin, but neither could pass-through by, say, 80 %), but also affects the point estimates, suggesting that an aggregation bias may be present as discussed in Geweke (1978). Based on the daily and weekly data, we would not reject the null hypothesis of full and equal pass-through for both types of inputs, but the power of the test is low particularly for the weekly data.

To learn about the variation in pass-through over time, I re-estimate (3) after interacting all variables with weekday-hour dummies, thus obtaining a different estimate of cost pass-through for every hour of the week as shown in Figure 8. The point estimates for pass-through do in fact vary throughout the week for both types of inputs, but the confidence intervals are so large as to render hypothesis testing for each hour meaningless. To increase the precision of these estimates while using load period differentiations that are less broad than the generic peak/offpeak load periods, I separate the week into periods of very low demand (from 11 p.m. to 5 a.m.), very high demand (from 10 a.m. to 4 p.m. on workdays, sometimes also referred to as "superpeak"), and medium demand (all remaining hours). Estimates of cost pass-through by these finer load periods are shown in the rightmost panel of Table 1. Carbon costs are fully passed through in all demand regimes, but fuel cost pass-through during high

Figure 8: Cost pass-through by weekday and hour



Note: Hour 1 starts at midnight on Monday, and hour 168 starts at 11 p.m. on Sunday

and medium demand is incomplete, thus strengthening the borderline results in the first panel. On the other hand, the null hypothesis of equal pass-through is strongly rejected for hours of very low demand, and at $p<0.07$ during hours of high demand. Taken together, it appears that carbon costs are passed through fully to electricity prices, but that the pass-through of fuel costs is incomplete with the possible exception of low-demand periods.

4.2 Pass-through based on prices

Estimation of cost pass-through in the existing literature is mostly based on input prices rather than marginal costs, because the latter are not readily available. To compare the two approaches, I regress electricity prices on input prices and a set of dummies as shown in (9). I focus on the hourly data for the remainder of the paper.

To identify cost pass-through, I use a heat rate for the average marginal coal and oil generators of 2.63, and of 2.0 for the average marginal gas generator (this corresponds to $\bar{hr}^i_m$), and an emission factor of 0.341 for coal, 0.202 for natural gas, and 0.267 for oil.[22] The results for the six considered load periods are shown in Table 2. The coefficients on natural gas and carbon prices are positively and significantly associated with electricity prices, whereas the coefficient on the coal price are not. The oil price coefficient is mostly statistically significant, but has a negative sign during high-demand hours.

Table 2: Results from the price model

	Generic load periods			Custom load periods[c]		
	Base	Offp.	Peak	Med.	low	high
Variables						
Coal	0.623	0.717	0.452	0.636	0.774	0.338
st.dev[a]	0.627	0.666	0.652	0.601	0.788	0.670
Gas	0.846	0.713	1.088	0.888	0.545	1.163
st.dev[a]	0.263	0.269	0.318	0.261	0.303	0.334
Oil	0.230	0.250	0.195	0.236	0.263	0.163
st.dev[a]	0.091	0.092	0.112	0.093	0.093	0.121
EUA	1.052	1.038	1.073	1.061	0.952	1.151
st.dev[a]	0.256	0.257	0.293	0.253	0.295	0.296
Hypothesis tests						
α_F	0.747	0.724	0.790	0.775	0.667	0.772
st.dev[a]	0.148	0.156	0.159	0.145	0.176	0.166
p (α_F =1)	0.087	0.076	0.187	0.122	0.058	0.169
α_A	1.769	1.651	1.991	1.793	1.429	2.257
st.dev[a]	0.686	0.651	0.846	0.656	0.698	0.975
p (α_A =1)	0.262	0.317	0.242	0.227	0.539	0.198
p (α_F = α_A)	0.210	0.238	0.221	0.192	0.373	0.183
Imputed marginal generation shares (point estimates)[b]						
Coal	31.7%	37.7%	21.8%	31.2%	44.2%	16.7%
Natural gas	56.6%	49.2%	68.9%	57.3%	40.9%	75.3%
Oil	11.7%	13.1%	9.4%	11.6%	15.0%	8.0%
Marginal generation shares based on dispatch model						
Coal	74.4%	77.6%	68.7%	73.8%	82.6%	65.1%
Natural gas	24.41%	21.26%	30.10%	24.92%	15.98%	34.59%
Oil	0.27%	0.26%	0.28%	0.30%	0.30%	0.10%

a: Standard errors computed with Newey-West estimator; b: Shares computed as $T_i/T = \beta_i/(\alpha_F \cdot \bar{hr}^i_m)$; c: "Low" refers to 11 pm - 5 a.m., "high" to 10 a.m. - 4 p.m. on work days, and "medium" to all other hours.

The point estimates for cost pass-through are not close to one, but we fail to reject the null hypothesis of complete cost pass-through by a wide margin for carbon, and more narrowly so for fuel costs, due to the large confidence intervals. The loss of precision is due to the

[22]These are generic heat rates used for the computation of dark and spark spreads and correspond to an efficiency of 38 % and 50 %, respectively. Changing the assumed heat rates from the generic values to the slightly more efficient rates of 2.5 (coal and oil) and 1.82 (gas), which are consistent the marginal heat rates computed by the merit order model, does not change the results qualitatively.

substitution of the hourly marginal cost information with the daily price information, which leads to a much lower power of the test. Note that lower levels of cost pass-through, say of 75 %, are also consistent with these results.

The difference between the structural and reduced-form results (in terms of point estimates) can be highlighted by comparing the imputed shares of marginal generation with the shares from the dispatch model, as shown at the bottom of the table. For all fuel types, the point estimates for the imputed shares differ widely from the computed ones.[23] These results imply that the identifying assumptions most likely do not hold, namely that fuel prices and unconditional heat rates are uncorrelated, although no definite proof for bias is possible due to the low precision of the estimates.

Last, Table 3 presents the results from four different spread regressions. For offpeak and low demand hours, the dependent variable is the dark spread (electricity price net of the fuel cost of a typical coal generator), whereas for peak and high demand hours, the dependent variable is the spark spread (electricity price net of the fuel cost of a typical combined-cycle gas plant). By assumption, fuel cost pass-through is complete, and coal, respectively gas, are assumed to be marginal for the entire load period under consideration.

Table 3: Spread regression results

	Dark spreak		Spark spread	
	Offpeak	Low dem.	Peak	High dem.
β_A	0.822	0.655	0.786	0.840
st.dev	0.188	0.249	0.239	0.277
α_A	0.917	0.731	1.945	2.080
st.dev	0.210	0.278	0.592	0.687
p (α_A =1)	0.692	0.332	0.111	0.116
N	22'080	8'580	12'240	6'126

Note: Standard errors computed with the Newey-West estimator using a lag order of one week; low and high demand hours as defined in text

The imputed level of carbon cost pass-through is closer to one for the dark spreads than for the spark spreads, which is not surprising given that the assumption of coal being on the margin is closer to being correct during all offpeak and low demand hours, than the same assumption for gas during peak and superpeak hours, as shown at the bottom of Table 2. Intuitively, dividing the coefficient on the allowance price by the emissions factor of gas, rather than some weighed average of gas and coal, yields an estimate for carbon cost pass-

[23]Note that the imputed shares are associated with large standard errors (not shown), and especially so for coal, since the regression coefficient associated with the coal price is not statistically significant.

through of about 200 %, which cannot be reconciled with theory. At the same time, the null hypothesis of full pass-through (i.e., of exactly 100 %) cannot be rejected due to the large standard errors.

5 Conclusions

I estimate the rate of pass-through for fuel and carbon costs in the German wholesale electricity market in the short run using hourly spot market data, under the identifying assumption of exogenous short-demand. By constructing a detailed supply curve of fossil-based electricity and intersecting it with the residual demand for fossil-based generation, I determine the marginal generator for every hour of the year, which allows me to identify cost pass-through directly via marginal costs.

I find that carbon costs are passed through fully to electricity prices, or at least nearly so. The lower bound of the confidence intervals suggest that carbon costs are passed through to wholesale electricity prices by at least 84 %–89 %, depending on the load period considered, with the range of central estimates given by 98 %–106%. In contrast, fuel costs appear to be passed through incompletely, with a central range of 89 %–94%, but with the possible exception of hours when demand is low. For all examined load periods, pass-through of carbon costs exceeds that of fuel costs, although the difference is not always statistically significant. Overall, the results suggest that carbon costs are passed through to a greater extent than fuel costs, which is consistent with the results reported by Fabra and Reguant (2014) in the context of the Spanish market. These authors explain incomplete fuel pass-through by ramping costs: During hours of low demand, firms prefer to bid low than having to take their plants offline. However, I find that fuel costs are passed through to a greater extent during hours of low demand than during peak and superpeak hours.

Another explanation for differential pass-through could be that the fuel prices used here do not adequately capture firms' opportunity costs. This may be true especially for coal, where many firms have individual contracts with suppliers, and for which various market prices exist (see, e.g., Rickels et al., 2014). Besides incomplete pass-through, a coefficient of less than unity on marginal fuel costs would be consistent with a situation where firms' true opportunity costs for fuel vary by less than the fuel costs computed with the generic fuel price indices; this is true even if firms' fuel costs are higher on average, because the (constant) difference would be absorbed by the intercept. However, to examine this possibility in more detail, information about firms' true fuel opportunity costs (including transactions costs to sell contracted fuel on the market) would be needed.

I compare my approach to various alternatives encountered in the literature, which, with the notable exception of Fabra and Reguant (2014), has estimated cost pass-through using prices rather than marginal costs, and which has not exploited the variation in demand and supply shocks by focusing on futures data. Cointegration frameworks furthermore tend to aggregate the data in order to reduce noise and to focus on long-run adjustments of prices to each other. I show that aggregating my data to a daily or weekly level not only reduces the precision of the estimates, but that there is some evidence for an aggregation bias.

Estimating cost pass-through based on input prices, rather than marginal input costs, implies a form of data aggregation even if hourly electricity prices serve as the dependent variable, because a set of hourly explanatory variables (marginal costs) is replaced by a set of daily ones (prices). The resulting standard errors are several times larger than those based on a truly hourly regression. Furthermore, I show that price regressions lead to biased estimates if the merit order (i.e., the sequence according to which generators are brought online) is correlated with input prices, as would be expected. Assuming complete fuel cost pass-through and regressing electricity spreads on allowance prices, another frequently-used method in the applied literature, opens yet another door for estimation bias if the identity of the marginal generator varies over the examined load curve, and if fuel cost pass-through is in fact not complete, as seems to be the case.

Not surprisingly, the price-based analyses, although mostly reporting positive rates of carbon cost pass-through, have not been able to determine the *level* of pass-through with satisfactory accuracy. My results provide the strongest evidence for full cost pass-through of carbon costs in the literature to date, thus validating the EU's decision to completely eliminate free allocation for Phase III for electricity producers. They also have implications for future carbon markets that include electricity production, such as the recently enacted cap-and-trade system in the United States, to the extent that the corresponding electricity markets have now become as competitive as the German market appears to have become in recent years.

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Appendix

Estimation bias in the price regression

If the heat rate and the emission factor of the marginal generator are not independent of fuel prices, we cannot factor out average heat rates and emission efficiencies. Re-writing (10) while again suppressing variable costs, trend and time dummies leads to

$$
\begin{aligned}
P_t &= \beta_C Coal_t + \beta_G Gas_t + \beta_O Oil_t + \beta_A A_t + \epsilon_t \\
\epsilon_t &= (\alpha_F hr_t^C - \beta_C) Coal_t + (\alpha_F hr_t^G - \beta_G) Gas_t + (\alpha_F hr_t^G - \beta_O) Oil_t \\
&\quad + \big(\alpha_A \sum_i hr_t^i ef^i - \beta_A\big) A_t + u_t
\end{aligned}
$$

In order for the $\beta's$ to be unbiased, the corresponding dependent variable has to be uncorrelated with the error term. For example, the coefficient of the coal price is unbiased if the following expression is zero:

$$
\begin{aligned}
E[Coal_t \cdot \epsilon_t] = {} & E[Coal_t^2 \cdot (\alpha_F hr_t^C - \beta_C)] \\
& + E[Coal_t \cdot Gas_t \cdot (\alpha_F hr_t^G - \beta_G)] \\
& + E[Coal_t \cdot Oil_t \cdot (\alpha_F hr_t^O - \beta_O)] \\
& + E\big[Coal_t \cdot A_t \cdot \big(\alpha_A \sum_i hr_t^i ef_t^i - \beta_A\big)\big] + E[Coal_t \cdot u_t]
\end{aligned}
$$

If the heat rate and the emission factor of the marginal generator are not independent of input prices, the parenthesis cannot be factored out of the expectation operators and replaced by their means; if this were possible, we would be back in the case where the correspondence between the $\beta's$ and the $\alpha's$ as defined in (11)-(12) holds, such that the parentheses, evaluated at their means, would be zero. However, if heat rates, emission factors and input prices covary, the above expression generally differs from zero, which in turn implies that the OLS estimate for β_C is a biased estimate for the marginal effect of the coal price on the electricity price. The same logic applies to the coefficients of the other input prices as well.

Adjustments to electricity demand and supply

For a small share of consumption, only monthly numbers are available. Between January 2010 and April 2013, monthly demand exceeded hourly demand aggregated to the monthly level by a factor of 1.14, and I therefore scaled the hourly consumption data by this factor. I excluded monthly data after May 2013 for scaling purposes, because there appears to have been a change in data collection procedure. For hourly hydro generation there is a similar problem, and I used a scaling factor of 2.17 based on a comparison with monthly data.

There is no information about hourly use of electricity for pumping water into storage reservoirs. Under the assumption that pumps only work during offpeak hours, I computed the average hourly pump demand by dividing the monthly entries in the ENTSO-E production table by 468, which is the average number of offpeak hours per month.

Building the generation portfolio

Comparison of the generation datasets from the German Environment Agency (UBA), containing generators starting at 100 MW, and the Bundesnetzagentur (BNETZA) that contains generators as small as 10 MW, implies that the coal information in the UBA dataset is complete (i.e., no small coal plants exist). However, 4,159 MW of natural gas capacity, 1,375 of oil capacity and 670 MW of generation capacity based on process gas are missing, because the corresponding generators have an installed capacity of less than 100 MW. The BNETZA dataset does not contain technological information other than the fuel source, and I therefore have to make some assumptions based on the technology distribution in the UBA dataset. I add 1,000 MW of conventional gas, 2,000 MW of open-cycle gas turbines, and 1,159 of combined-cycle gas turbines, 1,375 of conventional oil, 300 MW of process gas with combined-cycle technology and another 370 with conventional technology, which brings the total capacity of my generation portfolio to 59,340 MW.

I computed the efficiency of each plant based on its fuel type, technology and year of build (or major retrofit, if applicable), using empirically derived formulae presented in Schröter (2004). For the relevant year, I use a weighted average of the original year of build and the year of a major retrofit, the underlying assumption being that retrofitting a plant in a given year increases its efficiency, but to a lesser extent than if the plant were built from scratch.

The efficiencies η as a function of plant age y for different technologies are given by

Hard coal:	$\eta(y) = 0.2982 \cdot (y - 1950) + 28.821$
Gas, CCGT:	$\eta(y) = \frac{20 \cdot (y - 1980)}{30} + 40$
Gas and oil, OCGT:	$\eta(y) = \frac{6.5 \cdot (y - 1980)}{25} + 32.5$
Gas and oil, conv.:	$\eta(y) = 44 \cdot \frac{0.2982 \cdot (y - 1950) + 28.821}{42.24}$
Relevant plant age:	$y = \big[y(orig.) + 3 \cdot y(retrofit)\big]/4$

Besides fuel and carbon costs, generation of electricity also entails some other variable costs due to such things as enhanced maintenance and lubrication, but excluding labor, which is assumed to be fixed. I assign all coal generators a variable cost of 2 €/MWh and of 1 €/MWh for gas and oil generators in the UBA dataset, and of 3 €/MWh for plants with less than 100 MW capacity.

I further make two adjustments. First, I assign an artificial marginal cost of 1 €/MWh to industrial plants, because they are presumably operate based on production needs rather than the cost of electricity. Because industrial plants do not typically run all the time, I assign them an average output of 70 % of the installed capacity. Second, I assign plants that are clearly identified as operated based on heat rather than electric output a marginal cost of zero generation during the heating months (October through April) and again assume an average use of 70 % of installed capacity. Based on the marginal costs of supplying electricity alone, there would be no oil generation at all, which contradicts the hourly generation numbers for oil (partial coverage only) by EEX Transparency.