Pass-Through of Emissions Costs in Electricity Markets*

Natalia Fabra
Universidad Carlos III and CEPR

Mar Reguant
Stanford GSB and NBER

February 27, 2014

Abstract

We measure the pass-through of emissions costs to electricity prices. We perform both reduced-form and structural estimations based on optimal bidding in this market. Using rich micro-level data, we estimate the channels affecting pass-through in a flexible manner, with minimal functional form assumptions. Contrary to many studies in the general pass-through literature, we find that emissions costs are almost fully passed-through to electricity prices. Since electricity is traded through high-frequency auctions for highly inelastic demand, firms have weak incentives to adjust markups after the cost shock. Furthermore, the costs of price adjustment are small.

JEL classification: L13, L94, D44.

*We thank the editor and two anonymous referees, who have greatly contributed to improve the paper. We are grateful to Peter Eccles, Denny Ellerman, Jose-Antonio Espín, Joe Harrington, Koichiro Ito, Matti Liski, Thierry Magnac, Martí Mestieri, Juan Pablo Montero, Nancy Rose, Stephen Ryan, Juan Toro, Michael Waterson and Ali Yurukoglu for helpful comments. We are grateful for the contribution of Antonio Jesús Sánchez-Fuentes to this project. Last, we want to thank seminar audicences at CEMFI (Madrid), EARIE Conference (Rome), Jornadas de Economía Industrial (Murcia), 5^{th} Atlantic Workshop on Energy and Environmental Economics (La Toja), University of Arizona (Tucson), the Berkeley-Stanford IO Fest (2011), Toulouse School of Economics, UC Davis, University of Michigan, Columbia University, and Yale University. E-mails: natalia.fabra@uc3m.es and mreguant@stanford.edu.

1 Introduction

Cost pass-through, namely the change in prices resulting from a cost shock, is an important concept in Economics. In Industrial Organization, the analysis of pass-through sheds light into a wide range of topics, including the welfare effects of price-discrimination (Aguirre et al., 2010), merger assessment (Jaffe and Weyl, 2013), or the quantification of cartel damages (Verboven and van Dijk, 2009); in International Economics, a key question is whether exchange-rate fluctuations are passed-through to the prices of imported goods (Goldberg and Knetter, 1997); and in Public Economics, pass-through is central to the theory of tax incidence (Marion and Muehlegger, 2011).

From an empirical perspective, the measurement of pass-through has proved challenging mainly because marginal costs and markups are typically non-observable. The common approach is to first estimate demand parameters, and then back-out markups from the first order conditions of profit maximization. However the implications of modeling choices for pass-through remain an open empirical question (Goldberg and Hellerstein, 2008). This is particularly relevant in oligopolistic settings, as under imperfect competition the curvature of demand - and not only its elasticity - may have a profound effect on the quantification of pass-through (Weyl and Fabinger, 2013).[1] In this paper, we measure and explore the determinants of the pass-through of emissions costs to electricity prices. We do so using a framework that relies on minimal assumptions on the shape of the demand curve and on firms' strategic behavior.

The availability of high frequency and highly disaggregated data make electricity markets a uniquely suited setting for a pass-through analysis. Electricity markets are organized as auctions, which enables us to observe not only market clearing prices and quantities, but also the hourly demand and supply schedules. Furthermore, it is possible to construct reliable engineering-based marginal cost estimates, given that the electricity production function is well known and fossil fuels are traded in international markets. Marginal emissions costs can also be measured very accurately, since these depend on the carbon price and on the emissions rate of the price-setting unit, whose identity is revealed by the bid data. Last, but not least, the institutions that shape firms' strategic behavior in electricity markets are well understood,[2] making it possible to construct structural models that mimic closely the way firms actually compete in these markets.

The cost shocks induced by changes in carbon prices, as opposed to changes in other cost components, are also particularly suitable for an empirical analysis of pass-through. First, the effects of carbon prices on the marginal costs of generating electricity are significant and vary both across time as well as across technologies. And second, fluctuations of emissions permit prices are a source of plausibly exogenous cost shocks to firms (at least in a partial equilibrium sense) since pollution permits are traded across many countries and sectors.

In our empirical analysis of pass-through, we use data from the Spanish wholesale electricity

[1] For instance, see Bulow and Pfleiderer (1983) for an analysis of tax pass-through in the tobacco industry and the importance of the demand functional form assumptions. More generally, the dependence of mark-up estimates on the assumed functional forms has been acknowledged by the empirical IO literature (see e.g. Bresnahan (1982, 1989), Reiss and Wolak (2007), and Kim and Knittel (2006), among others).

[2] See the seminal papers by Green and Newbery (1992) and von der Fehr and Harbord (1993), among others.

market covering the period in which the European cap-and-trade program for carbon emissions was introduced.[3] We focus on pass-through in the wholesale market given that retail prices are regulated and therefore invariant, at least in the short-run, to changes in production costs.

We follow an instrumental variables approach to measure the effects of an increase in emissions costs on electricity market prices. We find the average pass-through in this market to be above 80%, implying that a one euro increase in emissions costs translates, on average, into an increase in electricity prices of more than eighty cents. If we separate the estimates between hours of low and high demand, we find that firms are more able to pass-through costs in high demand hours, when dynamic constraints are less relevant. In fact, this estimate goes up to 100% during peak times when firms face no start-up costs.[4]

In the broader pass-through literature, the finding of an almost complete pass-through is the exception rather than the rule. A great number of studies have measured the pass-through of exchange-rates to prices of imported goods, and they robustly report pass-through estimates lower than fifty percent, if not less. For instance, in the beer market, Goldberg and Hellerstein (2013) document that only 5% of an exchange rate change is transmitted to final prices; similarly, in the coffee industry, Nakamura and Zerom (2010) report a long-run pass-through elasticity of commodity prices of 25%.[5]

Given our finding of an almost complete pass-through, it is natural to ask: Why is the pass-through so high in electricity markets? Are the channels of price-through incompleteness identified in other settings not relevant in ours? And, are there other relevant channels?

The pass-through literature has identified three main channels of pass-through incompleteness: (i) the strategic adjustment of markups due to cost shocks, (ii) the presence of certain costs that remain unaffected by the observed cost shock (the exchange-rate pass-through literature refers to these as *non-traded costs*), and (iii) the presence of price rigidities that restrict firms from adjusting prices optimally. A robust conclusion of the literature is that non-traded costs are the main source of incomplete pass-through, followed by markup adjustment (Goldberg and Hellerstein, 2008). Nominal price rigidities might delay price adjustment, but otherwise have a minor impact on the long-run pass-through (Nakamura and Zerom, 2010; Goldberg and Hellerstein, 2013).

To the list of potential channels we add an additional one, namely (iv) the mismatch between observed cost shocks and firms' actual opportunity costs. This could be an important source of incomplete pass-through in the presence of transaction costs in input markets. This mismatch could also arise if firms are not fully equipped to understand the value of opportunity costs.[6] In

[3]See Ellerman et al. (2010) for a description of the European cap-and-trade program.

[4]This evidence is consistent with the results reported in other studies in the context of the European cap-and-trade program. Sijm et al. (2006) estimate pass-through rates using equilibrium prices and fuel cost data in the German electricity market, and find pass-through rates that range between 0.60 and 1.17, depending on market conditions. See the Annex by Keppler in Ellerman et al. (2010) for a review of this and other studies. These studies are based on market outcomes, in contrast to our analysis, which uses finer micro-level data. See Bushnell et al. (2013) for related evidence.

[5]See also Bonnet et al. (2013), Goldberg and Verboven (2001) and Hellerstein (2008), among others.

[6]Nakamura and Zerom (2010) argue that firms might respond differently to changes in commodity prices versus fluctuations in exchange rates because of limited information capacity (Mackowiak and Wiederholt, 2012). They

our setting, we show that we can infer firms' actual costs from their bidding behavior, and separately identify them from their equilibrium effect on prices.

We propose a variety of tests to quantify the relevance of these channels. Within a structural framework that is commonly used in the electricity auctions literature (see Wolak (2000) and Hortaçsu and Puller (2008), among others), we first test if firms' behavior is consistent with full internalization of permit prices. We cannot reject that the emissions price reflects the actual cost of emissions permits. Interestingly this finding shows that the Spanish electricity firms fully incorporated the opportunity cost of permits, despite the fact that the emissions market had just been created and firms did not participate very actively in it. This is also consistent with the allocation of free permits having no distortionary effects in the short run.[7]

To assess the incentives for markup adjustment, we use the same structural model to develop a first-order approach that decomposes the pass-through after a one euro increase in emissions costs. Price changes are driven both by changes in marginal costs and changes in markups. The high correlation of cost shocks across firms together with the highly inelastic nature of aggregate demand implies that the incentives to adjust markups are very weak in these markets. As a consequence, prices tend to move one-to-one with changes in emissions costs.

Next, we show that our measured pass-through is not affected by the presence of other cost components that do not depend on the emissions price. In our baseline model, we use a linear specification for the pass-through regression while controlling for the presence of other costs since (i) emissions costs enter the cost function in a linear fashion, (ii) we are able to measure these costs with high precision and (iii) we observe the other components of marginal costs. This implies that our pass-through estimate is already net of non-emissions costs. Given that we observe total marginal costs, we can also measure their pass-through to final prices. We find consistent results as compared to when we measure the pass-through of marginal emissions costs only, thus highlighting the advantages of having detailed micro-level cost data.

Last, price rigidities might be a source of incomplete pass-through, as they might limit firms' ability to adjust prices optimally (Nakamura and Zerom, 2010; Goldberg and Hellerstein, 2013). Intuitively, the costs of price adjustment in electricity markets are likely to be small given that firms have to participate in the electricity auction on a daily basis. However, if there are some costs of bid preparation, firms might prefer not to update their bids as often as allowed to do so. A close look at the data reveals the presence of very small price rigidities. Indeed, firms change their bids frequently, about 80% of the days on average. This frequency is even higher for Mondays and Saturdays, when the payoffs from bid adjustment are enhanced by weekday-weekend demand variation.

In conclusion, the institutional framework of electricity markets stands as the main factor

acknowledge that such a "cognitive divide" in decision-making may play a role in explaining incomplete pass-through, but decide to abstract from it.

[7]See also Reguant and Ellerman (2008), Fowlie (2010) and Kolstad and Wolak (2008) for related evidence on whether firms internalize emissions costs. The last two report a situation in which short run incentives are distorted, so that the opportunity cost is not given by the permit price.

explaining our high measured pass-through. In particular, since electricity is traded through high-frequency uniform-price auctions for an almost perfectly inelastic demand, firms have weak incentives to adjust markups after a cost shock. In addition, the auction mechanism provides very detailed data, which is crucial for our estimation strategy. Finally, the costs of price adjustment are relatively small. The fact that most other markets analyzed in the pass-through literature are organized through bilateral negotiations contributes to explaining why our measured pass-through rate is higher than usual. In this sense, the auction mechanism, unlike other market institutions, proves efficient in almost instantaneously passing through changes in input costs to wholesale prices.

Our results have important policy implications. Since January 2013, full auctioning of emissions permits has become compulsory for the power sector. The finding that firms internalize the value of free permits suggests that the short run effects of a system with taxes or without grandfathering should not differ much from the one with free allowances.[8] In contrast with the conventional wisdom, the use of auctions to allocate permits should not have any additional inflationary effects on electricity prices, at least in the short run.[9]

Furthermore, the high measured pass-through rate suggests that the introduction of emissions regulation implies a wealth transfer from consumers to producers, not only because of the free allocation of permits, but also due to increased market prices. Full auctioning of emissions permits will thus not remove these gains from the existing non-polluting technologies.

The paper proceeds as follows. Section 2 describes the context and data of the analysis. In Section 3, we measure the pass-through rate by means of a reduced-form regression. In Section 4, we present a structural framework to explore the role of demand, supply and markup adjustments in explaining the pass-through. We also explore whether and how the cost decomposition affects the pass-through estimates, and measure the extent of price rigidities in this market. Section 5 concludes.

2 Context and Data

2.1 The Context

We study the pass-through of emissions costs to wholesale electricity prices in the Spanish electricity market. We focus on the period from January 2004 to February 2006, which comprises the first phase (2005-2007) of the European cap-and-trade program for carbon, known as the European Union's Emissions Trading System (ETS).[10] The ETS is currently the largest carbon market in the

[8] See Fowlie et al. (2012) for a situation in which grandfathering can have long run impacts on investment, entry and exit decisions.

[9] A high UK government official stated that "[Auctioning permits] is ultimately going to show up in higher prices for goods, most obviously higher energy prices," Harvey and Eaglesham (2008). See also the response by Klemperer (2008).

[10] We do not include the period from March 2006 onwards because there was an important regulatory change in the Spanish electricity market (Royal Decree-Law 3/2006) that distorted the market clearing procedure in the auctions. It implied that market prices would only be paid to firms' net sales; more specifically, firms' production covered by the purchases of their downstream subsidiaries would be bought and sold at a regulated price. We have experimented

world, and it is the European Union's flagship instrument to fight climate change.[11]

Under cap-and-trade, the total amount of emissions is capped, and emissions permits summing up to the cap are distributed among pollutants. On a yearly basis, emitters are required to surrender a permit for each tonne of carbon they emit. For this purpose, they can either use their own permits or they can trade them in the OTC market or through exchanges. During the first and second phases of the ETS, emissions permits were distributed almost entirely for free.[12]

One half of total regulated emissions in Europe come from the power sector as thermal plants burn fossil fuels (coal, gas and oil) to generate electricity. Under the new emissions regulation these plants now face a cost for carbon. In Spain, which is the focus of our paper, thermal units produce approximately 50% of total electricity production during the sample period. The other technologies for electricity generation are nuclear (20-25%), traditional hydro power (8-11%), and renewable resources (9-12%), all of which are carbon-free.

There are 89 thermal units subject to emissions control, 36 of which are coal plants, 38 are new combined cycle gas plants, and 15 are traditional oil and gas plants. The average emissions rate of coal plants is 0.95 tons/MWh, although this rate varies across units depending on the type of coal they burn as well as on their fuel efficiency levels. Combined cycle natural gas units (CCGTs) have much lower emissions rates, averaging 0.35 tons/MWh with little dispersion across plants. Since coal plants typically have lower marginal costs than CCGTs, on average they operate closer to their full potential (their capacity factors are 65% versus 37% over the sample). Finally, traditional oil-fired or gas-fired plants, which are more inefficient than newer gas plants, only operate at 7% of their capacity on average.

During the sample period, the Spanish electricity market was supplied by four vertically integrated incumbent firms, plus a set of small fringe players. Altogether, the four main incumbents own 61 of the 89 production units affected by the emissions regulation. Additionally, these firms also own nuclear and hydro plants, specially the two largest firms. In terms of total production, the market share of these two firms exceeds 80% during this period.

2.2 Overview of Prices

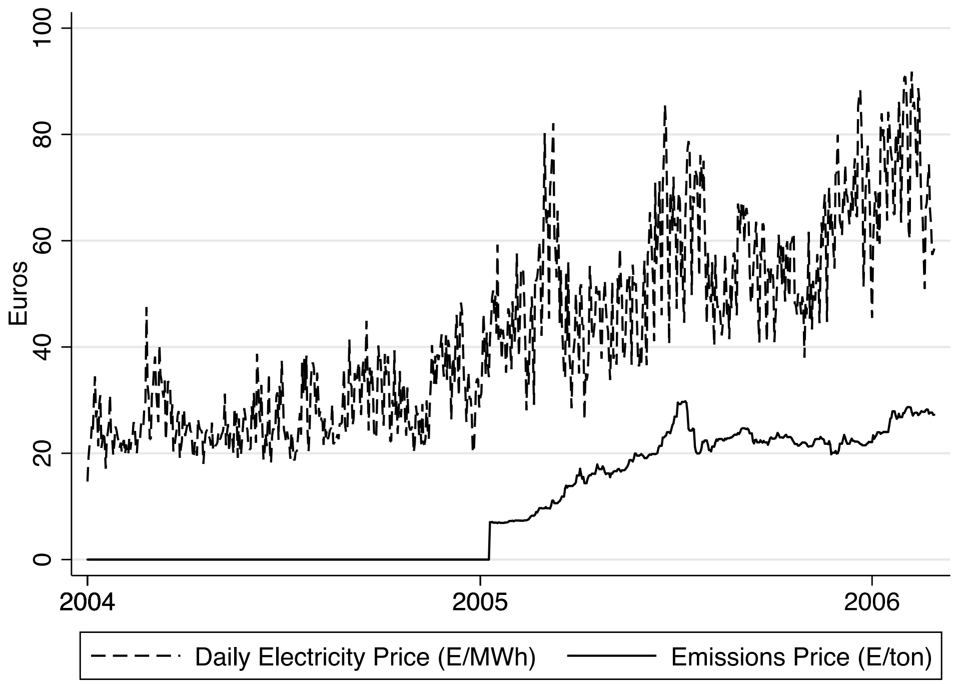
Since we will be measuring the pass-through of emissions costs to electricity prices, it is illustrative to provide a first look at their evolution over the sample period. As can be seen from Figure 2.1, electricity prices are highly volatile as a result of frequent changes in demand and supply conditions. Movements in demand display strong seasonal components (e.g., winter-summer,

including this period in the sample and the overall conclusions of the analysis hold.

[11]The first phase covered only carbon dioxide emissions from energy related industries (combustion installations with a rated thermal input exceeding 20MW, mineral oil refineries, coke ovens), production and processing of ferrous metals, the mineral industry (cement clinker, glass and ceramic bricks) and the pulp, paper and board industry. These activities represent around 40% of CO_2 emissions in the European Union. For more details on the EU ETS, see Ellerman et al. (2007) and Bahringer and Lange (2012).

[12]A few countries decided to auction a small share of permits, which was capped by law to be at most 5% of the total amount of permits (Ellerman et al., 2007). Since January 2013 (a period not covered in our analysis), full auctioning of permits has become compulsory for the power sector.

Figure 2.1: Evolution of the ETS Carbon Price and the Spanish Wholesale Electricity Price



weekday-weekend), and supply conditions vary with the availability of renewable resources (hydro and wind) and with changes in input prices (coal, gas, oil and carbon).

While the figure suggests that emissions costs affected electricity prices, it tells us little about the magnitude of the pass-through. We next describe the data set that enables us to perform a rigorous empirical analysis of the magnitude and determinants of the pass-through.

2.3 Supply and Demand Bid Data

We use detailed data on the bids submitted to the Spanish day-ahead electricity market from January 2004 to February 2006.[13] The day-ahead market concentrates approximately 70% of all electricity traded in Spain. It operates as a multi-unit uniform-price auction, similarly to other auction-based markets, e.g. the Treasury Bill market.

On a daily basis, electricity producers submit 24 hourly supply functions specifying the minimum price at which they are willing to produce a given amount of electricity at a given hour of the following day. Similarly, retailers and large electricity consumers submit 24 hourly demand functions specifying the price-quantity pairs at which they are willing to purchase electricity. The market operator orders the individual bids to construct the aggregate supply and demand functions for every hour, and the intersection of these two curves determines the market clearing price and quantities allocated to each bidder.[14] Sellers (buyers) receive (pay) the market clearing price times

[13]These data are publicly available at the system and market operator web sites, www.esios.ree.es and www.omie.es.

[14]These 24 hourly markets clear independently of each other, with one exception, the so-called "Minimum Revenue

their sales (purchases). Accordingly, for each of the 24 hours of the 790 days in the sample, we observe the price-quantity pairs submitted by each firm for each of their power plants.[15] We also observe all the price-quantity pairs submitted by the buyers.

Access to such a detailed and high-frequency bid data set presents several advantages. First, we observe the identity of the production unit that is actually setting the market price. This will be crucial throughout the analysis as it enables us to construct the relevant marginal costs and emissions costs data. Second, we can construct the hourly supply functions submitted by all firms in the market and the hourly residual demand functions faced by each firm. We can thus measure the slope of these curves directly so as to understand the role of markup adjustments in determining the pass-through (Section 4.1). Third, we observe the frequency of bid changes, which allows us to assess whether nominal price rigidities play any role in this market (Section 4.3).

2.4 Marginal Costs and Emissions Data

The marginal costs incurred by thermal plants can be decomposed into two elements: *marginal input costs* and *marginal emissions costs*. The former depend on the price of the fossil fuel used and the plant's "heat rate", i.e., the amount of energy used per unit of electricity produced. The latter depend on the carbon price and on the plant's "emissions rate", i.e., the amount of carbon emissions per unit of electricity produced.

To compute engineering estimates of *marginal input costs*, we use information on heat rates, fuel types, and variable operating and maintenance costs of all thermal plants in the Spanish electricity industry.[16] We also use publicly available information on coal, gas, and oil prices in international markets.[17] Our marginal cost estimates may contain some measurement error to the extent that plants' efficiency may have been upgraded, or the observed commodity costs do not reflect firms' actual input costs.

In order to estimate *marginal emissions costs*, we have collected annual information on carbon emissions at the plant level from the National Registry, for the years 2001-2004. These data are merged with the emissions data reported during the first phase of the European Trading System (2005-2007). We have thus estimated emissions rates at the plant level for each year, by dividing total emissions by total output. Emissions rates do not fluctuate much at the unit level and are consistent with typical fuel benchmark emissions for the generation plants involved (IEA, 2012).

Requirement", which allows bidders to withdraw their bids if their minimum revenue over the day is not above a given value. See Reguant (2013) for a complete treatment of the market algorithm.

[15] Supply functions can be made up to 25 price-quantity pairs for each production unit, even though in practice most units submit at most 5 or 6 steps. For thermal units, the average number of steps is 4.33 and the median is 3. At the aggregate level, the overall supply function of a big firm in a given hour can still contain over hundred steps.

[16] This information has been provided to us by the System Operator, which used to be in charge of dispatching production units according to their reported costs. We have updated this data set to include the new production units (mainly CCGTs). The same data are also used in Fabra and Toro (2005). The techniques used to compute engineering estimates of marginal input costs are similar to those in Wolfram (1999) and Borenstein et al. (2002), among others.

[17] For coal units, we use the MCIS Index, for gas units we use the Gazexport-Ruhrgas prices, and for peaking units we use the F.O.1% CIF NWE prices. All series are in €/te. We have obtained this information from Bloomberg.

Among coal units, imported coal plants have the lowest emissions rate, around 0.90 tons/MWh, whereas lignite units are the dirtiest, with an emissions rate ranging from 1.00 to 1.10 tons/MWh. Meanwhile, natural gas generators tend to have an emissions rate around 0.35 tons/MWh.[18]

In the empirical estimation, the relevant marginal emissions rate is that of the price-setting unit. Whenever such a unit is thermal, we use its emissions rate to compute the marginal emissions cost. If we do not observe the emissions rate of the unit exactly setting the price, we use data from the System Operator that reports the marginal technology at each hour. The definition of the marginal technology used by the System Operator is broader than ours, as it takes into account not only the unit exactly setting the price, but the marginal production units during a given hour. We set the marginal emissions rate equal to the average emissions rate of coal units if coal is reported marginal, and the average for gas plants when gas is reported marginal.[19]

Figure 2.2 reports the average marginal emissions rate in the market, as a function of the hour of the day. One can see that the marginal emissions rate is highest at night, when coal power plants are usually producing at the margin. During the day, emissions rates are lower, as demand is higher and gas plants produce at the margin. Consequently, marginal emissions rates are negatively correlated with market prices, since they tend to be higher in periods of low demand.

We combine emissions rates and spot permit prices to compute the marginal emissions costs. We use the spot permit price under the assumption that the emissions market is efficient, i.e., permit prices convey all relevant information. This implies that firms cannot make any informed arbitrage by either hoarding or overselling permits.[20] In our application, and given the small share of Spanish electricity emissions in the overall EU ETS market, we also assume that the Spanish electricity firms are price takers in the permit market.

3 Measuring the Pass-Through Rate

3.1 Empirical Framework

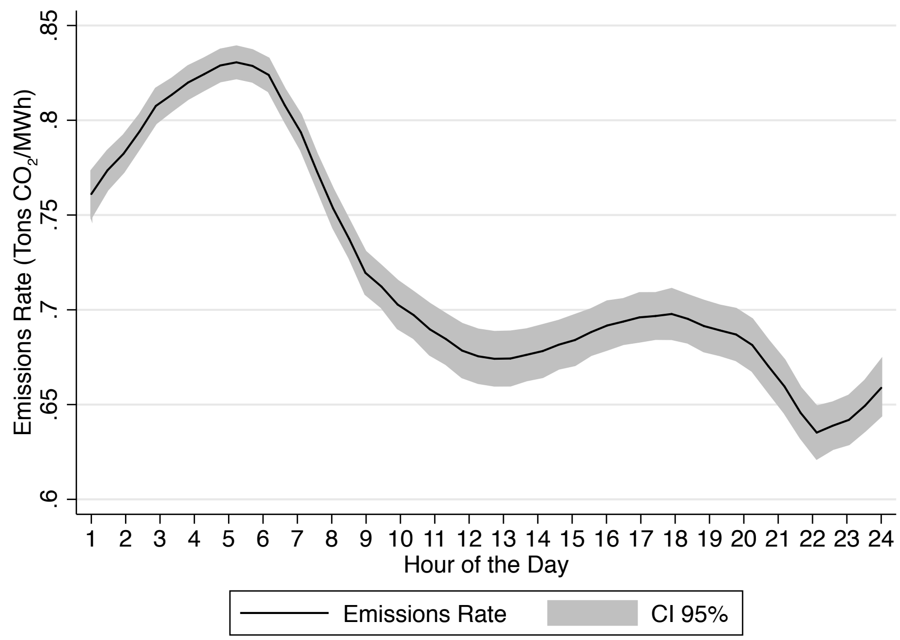
We use an instrumental variables approach to measure the equilibrium effect of a marginal increase in emissions costs on electricity market prices. In our baseline specification, the dependent variable is the hourly price of electricity (p_{th}), whereas the main independent variable is the marginal

[18] We include a more detailed description of the emissions data in the online appendix.

[19] Given that the Market Operator does not necessarily classify all hours as coal or gas only, there still remain 10% of the hours in which the marginal emissions rate is not observed. In the baseline regression, we exclude these hours from the sample. To complete all observations, we have experimented constructing the marginal technology by interpolating the marginal technologies reported by the Market Operator. For example, if coal is marginal at 2am and 4am, and pumped hydro storage is reported marginal at 3am, we would consider that coal is at the margin also at 3am. Note that hydro plants have no emissions, but tend to replace a thermal plant at the margin. Results are similar if we also include these additional observations. See Table A.3 in the Appendix.

[20] As supporting evidence to this assumption, we collect additional data from the EU ETS Transactions Log Register, which reports all permit trades during the period. We examine the transactions made by the Spanish electricity firms in our data set and find that they transacted very few times during the sample period. Had they had additional information not conveyed in market prices, they would have for instance sold permits before the collapse in prices that occurred in April 2006, but they did not.

Figure 2.2: Average Marginal Emissions Rate across the Day



emissions cost. Since the pass-through is an equilibrium outcome, we include additional exogenous demand and supply factors to control for other market forces that could affect market prices.[21]

The main specification is as follows:

$$p_{th} = \rho \tau_t e_{th} + X_{th}\beta_0 + X^D_{th}\beta_1 + X^S_{th}\beta_2 + \omega_{th} + \epsilon_{th}, \tag{3.1}$$

where ρ identifies the equilibrium cost pass-through. The emissions rate of the unit that sets the price at a given hour is captured by e_{th}, and τ_t represents the price of emissions permits. Therefore, $\tau_t e_{th}$ is the marginal emissions costs that firms face at a given hour h and day t. The controls X_{th}, X^D_{th}, and X^S_{th} stand for exogenous common, demand and supply controls, respectively, and ω_{th} is a vector of fixed effects.

The main specification includes month of sample, day of the week and hour fixed effects to control for potential trends and fluctuations. In some specifications, we also allow the hourly fixed effects to be different for every month, due to seasonal changes in sunlight and weather that affect electricity demand. As common controls, we include fossil-fuel prices (coal, gas and oil). On the demand side, we include economic activity indicators and weather controls. On the supply side, we include wind speed due to the presence of significant wind power generation in Spain.

When estimating this equation, it is important to realize that the hourly marginal emissions cost, $\tau_t e_{th}$, is likely to be endogenous. Indeed, the identity of the marginal unit, and thus the *marginal emissions rate* (e_{th}), is likely to be endogenous, as it is potentially affected by high-

[21] Busse et al. (2013) follow a similar approach when measuring the equilibrium effects of gasoline prices on car prices, while including both demand and supply controls.

frequency unobserved supply and demand shocks. The main variation in emissions rates comes from the technology side: coal plants are up to three times dirtier than natural gas plants. In turn, coal plants also tend to have lower marginal costs than gas plants. Hence, in periods of low demand, when electricity prices tend to be lower, coal plants are dispatched more often than gas plants, as already shown in Figure 2.2. If one did not account for the endogeneity of the marginal emissions rate, one could misleadingly attribute low prices to the higher emissions costs of coal plants. Not surprisingly, when we regress the market price on the marginal emissions cost, the pass-through rate is negative, ranging from -0.17 to -0.22.

To address this problem, we can use the emissions price, τ_t, to instrument for marginal emissions costs, $\tau_t e_{th}$. Conditional on the emissions price being exogenous, we can obtain a consistent estimate of the cost pass-through in this market. In fact, the emissions price is likely to be exogenous to the Spanish electricity companies. Emissions permits are traded across several countries and sectors in the European Union, of which the Spanish electricity sector is only a small part.

In a broader sense, the emissions price could still be endogenous to the Spanish electricity market due to common macroeconomic trends across the EU and due to general equilibrium effects of emissions prices on fuel cost and the electricity demanded by other sectors. We address this potential endogeneity by including a rich set of controls in the regression; notably, commodity prices. To address the potential concerns that could arise due to omitted variables bias, we also include month of sample fixed effects in all our specifications.[22]

3.2 Main Results

Table 3.1 reports our estimates of the pass-through rate. Column (1) presents the baseline results, with a pass-through estimate of 0.862. This implies that a one euro increase in emissions costs translates, on average, into an eighty-six cents increase in electricity prices. All the other covariates have the expected signs. On average, temperature is negatively correlated with electricity prices, with maximum temperature having a positive effect. This is consistent with electricity demand being higher during winter and in very hot summer days. Wind speed reduces electricity prices due to the presence of substantial renewable wind power in Spain. This effect is however partly reduced in very windy days, as wind mills need to be switched off when wind speed is too high. Consistently, we find a positive correlation between wind speed squared and electricity prices. Finally, coal and natural gas prices are positively correlated with electricity prices, whereas the correlation between the price of Brent and electricity prices is negative. This latter effect could be capturing some aggregate macroeconomic effects.

Specifications $(2)-(5)$ introduce several additional controls to the baseline regression. Column (2) allows the effect of temperature to have a different effect on price depending on the month of the year. This can be important, as a relatively warm day tends to reduce electricity consumption

[22] As an additional robustness check, we have estimated the regression with quarter-of-sample or bimonthly time trends, to capture macroeconomic fluctuations, and the results are robust. We find that, if we are too flexible on time trends and include month of sample time trends, emissions prices eventually do not exhibit enough remaining variation to identify the pass-through.

Table 3.1: Cost Pass-through Regression Results

	(1)	**(2)**	**(3)**	**(4)**	**(5)**
Mg. Emissions Costs (ρ)	0.862	0.860	0.835	0.829	0.848
	(0.181)	(0.182)	(0.173)	(0.172)	(0.168)
Temperature	-0.231		-0.204		
	(0.060)		(0.057)		
Maximum Temperature	0.137		0.112		
	(0.050)		(0.047)		
Wind Speed	-2.086	-2.171	-2.089	-2.191	-2.238
	(0.354)	(0.361)	(0.333)	(0.337)	(0.329)
Wind Speed Squared	0.055	0.066	0.054	0.067	0.068
	(0.025)	(0.025)	(0.023)	(0.023)	(0.023)
Coal	57.477	45.548	57.496	45.469	
	(4.035)	(4.364)	(3.885)	(4.164)	
Gas	5.638	3.589	5.604	3.563	
	(0.407)	(0.405)	(0.391)	(0.387)	
Brent	-2.896	-1.685	-2.938	-1.778	
	(0.881)	(0.985)	(0.834)	(0.930)	
F-test	124.8	114.0	129.9	119.3	118.3
MonthXTemp,MaxTemp	N	Y	N	Y	Y
MonthXHour FE	N	N	Y	Y	Y
HourXInput	N	N	N	N	Y

Notes: Sample from January 2004 to February 2006, includes all thermal units in the Spanish electricity market. All specifications include month of sample, weekday, and hour fixed effects, as well as weather and demand controls (temperature, maximum temperature, humidity), supply controls (wind speed and wind speed squared); and common controls (commodity prices of coal, gas, and oil). The marginal emissions cost is instrumented with the emissions price. Robust standard errors in parentheses. Number of observations: $16,186$.

during the winter, but to increase it during the summer. Column (3) introduces an hourly fixed effect for each month of the year to more flexibly control for seasonality due to temperature and also due to changes in day/night demand differences over the year. Column (4) combines both sets of controls. Finally, specification (5) allows the effects of commodity prices to be different depending on the hour of the day. The rationale behind this specification is that coal (gas) plants tend to be marginal during low (high) demand hours. Pass-through estimates are robust across specifications, with the pass-through being between 77 and 86%.[23]

A relevant question is whether the pass-through differs in peak versus off-peak hours. There are good reasons to suspect this is the case. Generators face several constraints when operating their plants due to ramping costs (i.e., the speed at which they can change their production), start-up costs, minimum load, or minimum downtime. This may affect pass-through, as it has an effect on firms' opportunity costs and hence on their pricing behavior. For instance, firms might find it optimal to bid below marginal costs to avoid switching off their plants (Mansur, 2008; Bushnell et al., 2008). Since these constraints are more likely to be binding during off-peak times, the main hypothesis is that the pass-through rate should be lower during these hours.

Table 3.2 presents estimates of the cost pass-through rates when allowed to differ for peak and non-peak hours. In all five specifications, the pass-through rate is approximately 60% during off-peak hours. The estimates for on-peak hours, on the other hand, are higher than the estimates in the baseline regression and very close to 100%. These results provide further evidence that the pass-through in this market was very high, particularly in those hours in which we would expect firms to price marginally. Except for non-peak hours, we are unable to reject full pass-through in all specifications.[24]

4 Understanding an Almost Complete Pass-Through

Our finding of an almost complete pass-through of emissions costs to wholesale electricity prices is the exception, rather than the norm, in the pass-through literature. In this section, we exploit the richness of our micro-level data to closely explore why cost pass-through is so high in this market.

4.1 Demand, Supply and Markup Adjustments

A standard explanation for incomplete pass-through is the presence of demand, supply and markup adjustments. In the presence of a cost shock, firms' incentives to increase or decrease prices are generally affected by the shape of the demand curve, the shape of marginal costs, other firms' cost shocks, and the nature of competition among firms. The contribution of markup adjustments to

[23]The Appendix includes additional regressions that allow for more flexible functional forms for temperature, wind speed and commodity prices, all of which are consistent with the above results. See Table A.2.

[24]Peak hours are defined as hours between 8am and 8pm, which is the period defined as peak for forward contracts. However, there could be substantial ramping of power between those hours. We obtain very similar results of full pass-through if we focus only on afternoon hours between 4pm and 8pm, or just 6pm, as in Puller (2007) and Hortaçsu and Puller (2008).

Table 3.2: Cost Pass-through Regression Results: Peak vs. Non-Peak

	(1)	(2)	(3)	(4)	(5)
Mg. Emissions Costs - Peak	1.085	1.083	1.055	1.051	1.107
	(0.185)	(0.185)	(0.178)	(0.177)	(0.175)
Mg. Emissions Costs - Off Peak	0.635	0.633	0.608	0.603	0.496
	(0.170)	(0.170)	(0.164)	(0.163)	(0.164)
MonthXTemp,MaxTemp	N	Y	N	Y	Y
MonthXHour FE	N	N	Y	Y	Y
HourXInput	N	N	N	N	Y

Notes: Sample from January 2004 to February 2006, includes all thermal units in the Spanish electricity market. Only peak hours are included (between 8am and 8pm). All specifications include month of sample, weekday, and hour fixed effects, as well as weather and demand controls (temperature, maximum temperature, humidity), supply controls (wind speed and wind speed squared); and common controls (commodity prices of coal, gas, and oil). The marginal emissions cost is instrumented with the emissions price. Robust standard errors in parentheses. Number of observations: $16,186$.

pass-through incompleteness has been documented in several studies (see Goldberg and Hellerstein, 2013, for a review).

Thanks to the richness of our bidding data, we can flexibly approximate the contributions of demand, supply and markup adjustments to pass-through. Instead of posing a fully-fledged structural model, we perform a structural decomposition using minimal assumptions, some of which we can test. In particular, we first test whether the cost shocks that we observe are consistent with firms' observed strategies. Next, we simulate the changes on firms' first order conditions triggered by emissions cost shocks to assess their incentives to adjust markups.

4.1.1 Structural framework

Following the electricity auctions literature, we use a structural model of bidding behavior to derive firms' first-order conditions of profit-maximization. The optimality condition takes the general form of

$$\text{bid}_{it}(q_{it}) = \text{mc}_{it}(q_{it}) + \text{markup}_{it}(q_{it}). \tag{4.1}$$

The equation states that firms set bids equal to their marginal cost of production plus a markup.

The *marginal cost* component, as explained above, is the result of a combination of emissions costs and input costs, i.e.,

$$\text{mc}_{it}(q_{it}) = \text{marginal emissions cost}_{it}(q_{it}) + \text{marginal input cost}_{it}(q_{it}),$$

both of which we can measure. Note that these cost components are allowed to differ both across as well as within firms.

We do not observe the *markup* component directly in the data, but we can construct it. From the first order condition of profit maximization,[25] the markup is given by,

$$\text{markup}_{it}(q_{it}) = \Big|\frac{\partial p_{it}(q_{it})}{\partial q_{it}}\Big| q_{it}^N,$$

where q_{it}^N is the net quantity sold by the firm, i.e., its production minus its vertical commitments (Bushnell et al., 2008), and p_{it} is the inverse residual demand a firm faces, i.e., it gives the resulting market clearing price if the firm produces q_{it}. A firm possesses greater market power the steeper the inverse residual demand it faces, given that a steep inverse residual demand allows the firm to raise the price with only a small reduction in output. Furthermore, the bigger the net quantity of a firm, the more it benefits from the price increase.

Our data enables us to approximate the two main terms of the markup component: firms' net quantities and the slopes of their residual demand curves. For the former, we subtract the firm's physical and demand side contracts (e.g. purchases of its downstream subsidiary) from its output.[26] For the latter, as it is common in the electricity economics literature, we can directly approximate the slope of the residual demand curves from the observed bid data (see Wolak, 2003; Hortaçsu and Puller, 2008; among others). Figure 4.1 depicts the residual demand curves faced by each of the four major firms in the Spanish electricity market. As shown in the graphs, residual demand curves are complex highly non-linear objects, with elasticities varying substantially along the curves. The data allow us to estimate the elasticities around the market price with great flexibility.[27]

4.1.2 Measuring opportunity costs

Once we have constructed all the components of the structural equation, we can test equation (4.1). More specifically, we estimate the following empirical equation in those hours in which firm i is setting the market price through its marginal unit j:

$$b_{ijth} = \gamma e_j \tau_t + \beta c_{jt} + \theta \widehat{m}_{ijth} + \epsilon_{ijth},$$

where b_{ijth} is the marginal bid of firm i when setting the price with unit j at hour h and day t, e_j is the emissions rate of unit j, τ_t is the daily price of emissions permits, c_{jt} are the unit-specific marginal input cost estimates, $\widehat{m}_{ijth}$ is the approximated markup, and ϵ_{ijth} is the error term, which could arise due to cost shocks at the unit level, modeling error and/or firm optimization error.

We need to make a modeling choice when estimating the structural equation, as the first-order condition is only valid (i) for units that set the price with positive probability, and (ii) when the

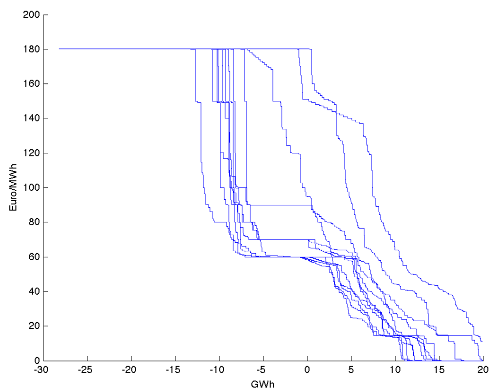
[25] See Wolfram (1998), Wolak (2003), Borenstein et al. (2002) and Hortaçsu and Puller (2008) for applications to the British, Australian, Californian and Texas market, respectively. See Reguant (2013) for a derivation in the context of the Spanish electricity market.

[26] To the extent that firms have additional financial contracts, the measured net quantity will generally be an upper bound of the actual net position.

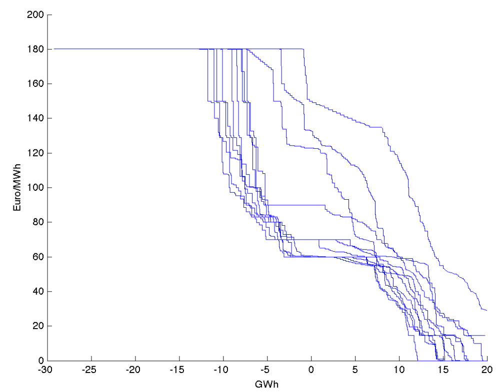
[27] As in Wolak (2003), we use a non-parametric smoothing Kernel estimator to approximate the slope of the residual demand curves.

Figure 4.1: Inverse Residual Demand Data

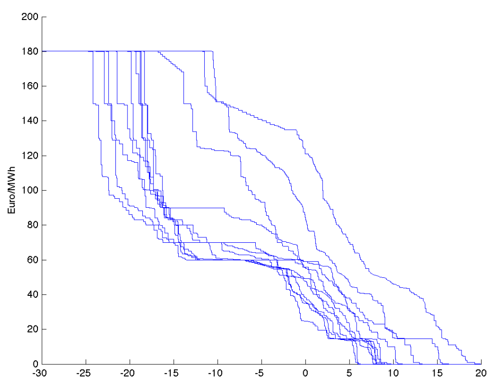
(a) Sample Inverse Residual Demands for Firm 1



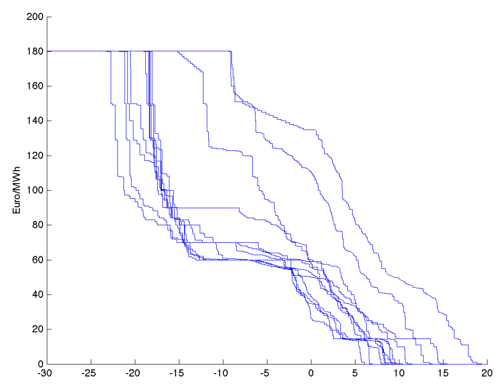
(b) Sample Inverse Residual Demands for Firm 2



(c) Sample Inverse Residual Demands for Firm 3



(d) Sample Inverse Residual Demands for Firm 4



Notes: Inverse residual demands faced by each firm at midday. For better comparison, the sample of random days is depicted across firms.

unit's capacity constraints are not binding. Accordingly, and for the sake of simplicity, we limit ourselves to those observations in which (i) units set the price ex-post, implying that they were indeed marginal, and to those observations in which (ii) the bid is not the first nor the last one in the unit's supply function, implying that they could indeed adjust their output.[28]

The main parameters to be estimated are β, γ and θ. Our focus of interest is testing $\gamma = 1$, which would imply that firms, on average, fully internalize the emissions permit price in their bidding decisions. It is important not to confuse the degree of internalization of permit prices (γ) with the resulting effect on equilibrium prices or pass-through rate (ρ). The former is a supply-side object reflected in firms' strategic behavior, while the latter is an equilibrium outcome resulting from the interplay of both supply and demand factors.

It is well known that tradable permits have an opportunity cost, namely, the price at which they can be sold at secondary markets, regardless of whether those permits were allocated for free or, more generally, regardless of the price paid for them. However, in our particular setting, several reasons have been put forward for why the price of the permits might not accurately reflect firms' opportunity costs of emissions. The first two explanations rely on firms being fully rational. For sellers of permits (which is the relevant case because of grandfathering), the opportunity cost of emissions is below the permits' market price (i) in the presence of transaction costs in the emissions market (Stavins, 1995), or (ii) under the expectation that future permit allocations will be based on current emissions (Fowlie, 2010). A third explanation rests on firms' limited information capacity (Mackowiak and Wiederholt, 2012): (iii) firms might be unable to understand that free permits have an opportunity cost (Goeree et al., 2010). More broadly, this can be an important test when some cost shocks are observed, but the way in which they enter the profit function might be unobserved or measured with error, as γ gives the structural estimate of how firms incorporate this cost shock in their behavior.

Table 4.1 presents our structural estimates. The estimation is performed at the industry level and at the firm level. Standard errors are clustered at the unit level.[29] All specifications include marginal cost estimates as a control. To the extent that this variable might not accurately reflect all relevant costs, we introduce unit fixed effects in specifications (2) to (4). Specifications (3) to (4) also include seasonal fixed effects. All specifications, except for specification (4), constrain the markup parameter to be equal to one ($\theta = 1$), as implied by the first order condition. In specification (4), we relax this constraint. Given that the markup depends on market demand and, thus, it is endogenous, we use weather data (temperature, wind speed, humidity) as residual demand shifters.

The estimated opportunity cost parameter γ is not distinct from one at the industry level and for the three largest firms in the industry. This finding is important on two grounds. First, it highlights the uniqueness of our cost shock for a pass-through analysis. Not only are permit prices

[28] As shown in Reguant (2013), firms use their non-marginal steps very differently in this market due to the interaction of dynamic costs and minimum and maximum capacity constraints.

[29] We present alternative clusters in the Appendix (see Table A.4). The implications of our results do not change substantially as a function of the degree of clustering.

exogenous to firms, but also they capture very accurately the cost shock they suffer. This rules out the possibility that a potential mismatch between the observed and the actual cost shock is biasing our pass-through estimates. Second, this finding is relevant from a policy perspective, since it implies that (i) transaction costs in this market are negligible, (ii) the permit allocation rule did not distort firms' short run incentives, and (iii) firms understood that free permits have an opportunity cost given by the permit price.

In contrast, the parameter estimates for β vary more across specifications and across firms. All estimates are very sensitive to the inclusion of the unit fixed effect, probably revealing the fact that the constant is capturing relevant costs not included in our marginal cost variable. Overall, it seems that firms do not respond at high frequency to changes in fossil fuel prices as they do to changes in carbon prices. One potential explanation is that, in many cases, fossil fuels are sold through take-or-pay long term contracts, implying that spot prices do not not always reflect the true opportunity cost of using the fuel.[30] Similarly, some regulations subsidize low quality national coal, which creates a mismatch between observed commodity prices and firms' actual opportunity costs of burning coal. In particular, national coal is of very low quality and it is not traded in international markets. Last, marginal production costs might not be as accurately measured as marginal emissions costs. For instance, coal has to be transported from either the national coal mines or from the harbor to the coal plants, whose locations differ.

Finally, the parameter estimate for θ appears to be broadly consistent with the structural model, although the relationship between markups and prices is particularly noisy for the smaller firms. This is in part explained by the fact that markups are much smaller for these firms. Whereas the residual demand that the two biggest firms face is quite inelastic, the residual demand curve that the other two firms face is substantially elastic, with average elasticities being 4.5 and 6.5, respectively. Reassuringly, the noise in the markup estimates has little bearing on the estimates on the internalization of marginal emissions costs (γ) and marginal input costs (β).

4.1.3 Measuring incentives for markup adjustments

Once we have confirmed that firms fully internalize emissions costs, we explore the implications of the emissions regulation on firms' strategies and market outcomes. As pointed out in the literature, the degree of correlation of cost shocks across firms, as well as the shape of demand and supply curves can have implications for pass-through. A firm's incentive to pass-through a cost shock is weaker if its rivals do not face the same shock. Similarly, if demand responds substantially to price increases, even a common cost shock across all firms can induce an attenuated pass-through due to movements along the supply and demand curves, as well as due to markup adjustments.

To assess these effects, we simulate changes on firms' best responses following a one euro increase in the carbon price. We use a first-order approach to simulate how optimal prices change.[31] A full

[30] Liquified Natural Gas (LNG) can be resold, thus implying that the relevant marginal cost is the price of gas regardless of the take-or-pay clause. However, this is not the case for gas coming through pipelines (which is the vast majority of the gas used in Spain).

[31] See Jaffe and Weyl (2013) for a derivation and application of the first-order approach in the context of mergers.

Table 4.1: Test based on structural equations

	All	**Firm 1**	**Firm 2**	**Firm 3**	**Firm 4**
Emissions cost (γ)					
(1) No FE	0.939	0.925	0.998	1.117	0.806
	(0.070)	(0.039)	(0.032)	(0.039)	(0.073)
(2) Unit FE	0.971	0.947	0.963	1.062	0.803
	(0.034)	(0.031)	(0.039)	(0.046)	(0.102)
(3) Unit FE + Season	0.957	0.959	0.963	1.008	0.784
	(0.034)	(0.028)	(0.027)	(0.053)	(0.085)
(4) Spec.3 + Markup (IV)	0.959	1.036	0.962	1.013	0.834
	(0.062)	(0.058)	(0.024)	(0.197)	(0.101)
Input cost (β)					
(1) No FE	0.812	0.476	0.892	0.952	1.037
	(0.047)	(0.029)	(0.021)	(0.021)	(0.014)
(2) Unit FE	0.598	0.494	0.303	0.821	0.643
	(0.064)	(0.057)	(0.055)	(0.037)	(0.053)
(3) Unit FE + Season	0.601	0.497	0.348	0.769	0.640
	(0.058)	(0.047)	(0.039)	(0.043)	(0.027)
(4) Spec.3 + Markup (IV)	0.604	0.487	0.335	0.773	0.683
	(0.069)	(0.038)	(0.060)	(0.172)	(0.114)
Markup (θ)					
(4) Spec.3 + Markup (IV)	0.973	0.515	1.037	0.934	-1.086
	(0.398)	(0.227)	(0.177)	(2.411)	(6.117)
Obs.	9,257	3,029	1,988	2,805	1,435

Notes: Sample from January 2004 to February 2006, includes all thermal units in the Spanish electricity market. Standard errors clustered at the unit level.

decomposition of the changes of equilibrium price as implied by a change in emissions costs in the first-order condition can be expressed as follows:

$$\Delta p = \underbrace{\underbrace{mc_1(q_0) - mc_0(q_0)}_{\text{Direct cost shock}} + \underbrace{mc_1(q_1) - mc_1(q_0)}_{\text{Cost shift due to } q}}_{\text{Cost change}} + \underbrace{\underbrace{\left|\frac{\partial p_1(q_1)}{\partial q_1}\right|\left(q_1^N - q_0^N\right)}_{\text{Markup change due to } q^N} + \underbrace{\left(\left|\frac{\partial p_1(q_1)}{\partial q_1}\right| - \left|\frac{\partial p_0(q_0)}{\partial q_0}\right|\right) q_0^N}_{\text{Markup change due to slope}}}_{\text{Markup change}},$$

where the index are used to refer to functions and market outcomes before and after the emissions cost shock. The first term is the direct cost shift from an increase in emissions costs. The second term accounts for the fact that an increase in costs can change the optimal quantity produced by the firm. Because marginal costs are not necessarily constant within each firm, this can induce a change in marginal costs. The third term implies that a change in the firm's quantity can increase or decrease the firm's inframarginal quantity, and thus affect its markup. Finally, the fourth term captures the fact that the slope of the residual demand can also change, due to two reasons: first, the firm's quantity might be different; and second, the residual demand itself may change as a result of an increase in the emissions costs faced by other firms.

Computing the endogenous changes in these components in a full structural fashion can be a difficult task, due to the fact that the first-order conditions across all firms are a highly non-linear system of differential equations. The supply function nature of the game is also known to potentially suffer from multiple equilibria (Klemperer and Meyer, 1989). Generalizing the computation of such equilibria is beyond the scope of this paper. Instead, we use a simplified methodology that allows us to conclude that, in the context of electricity markets, markup adjustments are indeed small.

We proceed by first assuming that markups are unchanged (last two terms), and thus firms only shift their supply curves by their emissions rates. With that shift, we can endogenously compute changes in prices due to marginal cost changes (first two terms).[32] We then check whether firms' incentives to adjust markups are indeed small by checking that, at the margin, demand changes are small, reshuffling of production across firms is limited, and the slopes of the residual demands do not change significantly.

Table 4.2 shows the changes in quantities, slopes of residual demands and markups, after a one euro increase in carbon prices. As can be seen in the table, aggregate demand response is very limited, which is consistent with demand being very inelastic in the short run. Quantities within the firm also remain very stable, which is consistent with emissions cost shocks being highly correlated across firms at the margin.

These two facts - inelastic aggregate demand and very correlated cost shocks across firms - suggest that firms have limited incentives to adjust markups. In fact, as shown in Table 4.2, the markups suffer little changes on average, as implied by the small changes in the slopes of the residual

[32]Figure A.1 in the Appendix shows the perturbed optimal strategies around the equilibrium price. This perturbation of optimal strategies is only valid at the margin. Given that the change in emissions costs is small, we take participation decisions as given. Characterizing the optimal startup decision is beyond the scope of this paper. See Reguant (2013) for a computation of optimal best responses in the presence of startup costs.

Table 4.2: Percent Changes in Quantities, Markups and Slopes

	Mean	SD	P25	P50	P75
Changes in Quantity					
Aggregate Demand	-0.2%	0.3%	-0.2%	0.0%	0.0%
Firm 1	-0.3%	1.3%	0.0%	0.0%	0.0%
Firm 2	-0.2%	0.8%	0.0%	0.0%	0.0%
Firm 3	-0.3%	7.1%	0.0%	0.0%	0.0%
Firm 4	-0.3%	1.2%	0.0%	0.0%	0.0%
Changes in Slope of Inverse Residual Demand					
Firm 1	1.1%	7.1%	-2.0%	0.8%	4.1%
Firm 2	0.3%	7.0%	-2.5%	0.2%	3.1%
Firm 3	0.9%	7.0%	-2.0%	0.6%	3.7%
Firm 4	0.8%	6.8%	-1.9%	0.5%	3.5%
Changes in Markup					
Firm 1	-0.9%	9.6%	-4.5%	-1.0%	1.9%
Firm 2	0.1%	10.3%	-3.3%	-0.3%	2.5%
Firm 3	-0.7%	12.3%	-4.2%	-0.8%	1.9%
Firm 4	-0.6%	10.1%	-3.9%	-0.7%	1.9%

Notes: Sample from January 2004 to February 2006, includes all thermal units in the Spanish electricity market. Table expresses percent changes in quantities, markups and the slope of the inverse residual demand for a one euro increase in carbon prices. Number of observations: 18,960.

demands and firms' quantities. Even though the slopes of the residual demands are relatively noisy and sensitive to the perturbation on the supply schedules, on average the changes are very limited and the resulting markups change by less than 1%. Since markups tend to be a relatively small fraction of the price, a 1% change in the markup implies an even smaller price change.

4.2 Emissions Costs *vs.* Non-Emissions Costs

In our baseline regressions, we have used a linear model to estimate the pass-through. Depending on the nature of the cost shock, either a linear or a log-log regression might be more suited. For example, in the exchange-rate pass-through literature, the cost shock that is observed affects costs multiplicatively through its impact on the terms of trade, making the log-log specification more suited. In these occasions, the researcher typically does not observe the weight of other costs not affected by exchange rate fluctuations, often called *non-traded* costs. As stressed in the exchange rate pass-through literature, the presence of non-traded costs is an important source of pass-through incompleteness.[33]

In the context of electricity markets, emissions costs also represent a small share of total costs (on average only 15-30% of total marginal costs during this period). Hence, a log-log specification using only marginal emissions costs would also reflect an incomplete pass-through. Fortunately, emissions costs enter linearly into the cost function. Therefore, we can use a linear specification for the pass-through regression, while flexibly controlling for the presence of other cost shifters. This approach does not directly deliver a pass-through elasticity, but has the advantage of being unaffected by the relative share of unobserved costs, as long as one can appropriately control for them in the regression.

Instead of using emissions costs only, one could alternatively estimate the pass-through rate using *total* marginal costs.[34] The log-log regression would then not suffer from incompleteness due to the presence of non-emissions costs. In our case, and thanks to our detailed data, we can compute total marginal costs using engineering marginal cost estimates. The emissions price is still a valid instrument for total marginal costs, as total marginal costs are the sum of both marginal input costs and emissions costs.

The linear and log-log specification are still not directly comparable, even if one uses total marginal costs, as the former is estimating a cent-to-cent pass-through and the latter is estimating an elasticity. In order to illustrate the differences between these specifications, it is useful to consider a numerical example. Suppose that total marginal costs are 35€, of which emissions costs are only 5€, and that the actual market price is 40€.[35] Assume that there is complete cent-to-cent pass-through, as suggested by our linear estimates. For a one euro increase in emissions costs, the market

[33] Goldberg and Hellerstein (2008) report that in existing studies non-traded costs contribute 50 to 78% to incomplete pass-through.

[34] The suitability of this alternative approach might be industry specific and/or data dependent. For example, this is the approach followed in DeLoecker et al. (2012), who are able to recover total marginal costs using detailed census data on output, prices and expenditures.

[35] In the example, markups are 14%. Average markups in this market (at the margin) have been estimated to be between 5% to 20% (Reguant, 2013).

Table 4.3: Emissions vs. Non-Emissions Costs: Peak vs. Non-Peak

	Emissions Costs		**Total Mg. Costs**	
	Linear	Logs	Linear	Logs
Peak Pass-Through	1.045	0.146	0.893	0.799
	(0.174)	(0.038)	(0.120)	(0.156)
Off-Peak Pass-Through	0.453	0.094	0.218	0.268
	(0.162)	(0.036)	(0.089)	(0.124)

Notes: Sample from January 2004 to February 2006, includes all thermal units in the Spanish electricity market. Only peak hours are included (between 8am and 8pm). All specifications include month of sample, weekday, and month-hour fixed effects, as well as weather and demand controls (temperature, maximum temperature, humidity), supply controls (wind speed and wind speed squared); and hourly linear (logarithmic) controls for commodity prices of coal, gas, and oil). (Log of) Costs are instrumented with (the log of) the emissions price. Robust standard errors in parentheses. Number of observations: $13,536$.

price becomes 41€. With a linear specification, we would compute a 100% pass-through rate. In contrast, the log-log calculation using emissions costs would deliver a pass-through of 12.5%, given that emissions costs have gone up by 20%, but the market price only by 2.5%. Finally, the log-log calculation using total costs would deliver a 87.4% pass-through rate, since total costs have increased by 2.86%, whereas market prices only by 2.5%.[36]

In Table 4.3, we estimate pass-through rates both in levels and in logs, for marginal emissions costs and total marginal costs. The differences across specifications highlight the advantages of having detailed cost data. The linear specification using total marginal costs provides relatively similar estimates as those obtained when emissions costs are used instead (linear), although they are somewhat lower.[37] When one looks at the log-log estimates, the picture is very different. The pass-through rate is much smaller if one only uses emissions costs, as emissions costs represent a small share of total marginal costs. On the contrary, the difference between the linear and the log-log specification using total marginal costs appears to be consistent with the level of markups in this market, as suggested by the above example.

In sum, our estimates of pass-through are broadly consistent with each other across linear and log-log specifications, given the share of emissions costs and the levels of markups in this market. The estimates are consistent across specifications with the hypothesis of complete cent-to-cent pass-through in peak hours, and the hypothesis that marginal costs are not fully priced at night, when dynamic production constraints are most binding.

[36] The incompleteness in the log-log calculation arises due to the fact that there are markups in this market, and full cent-to-cent pass-through only translates into full pass-through elasticity if markups are zero.

[37] This could be partly induced by potential non-classical measurement error in our marginal costs estimates, as suggested by our findings in Section 4.1. In particular, our engineering marginal costs appear to be larger than actual input costs, specially for Firm 1.

Table 4.4: Frequency of Bid Changes

	Previous Day Unit-Level	Previous Week Unit-Level	Previous Day Firm-Level
All days	0.375	0.710	0.795
Monday	0.490	0.705	0.907
Tuesday	0.304	0.691	0.774
Wednesday	0.276	0.682	0.719
Thursday	0.277	0.691	0.694
Friday	0.287	0.697	0.713
Saturday	0.605	0.739	0.932
Sunday	0.392	0.764	0.831

Notes: Table reports the average frequency of times in which the average price bid of a given unit changes. The average bid is defined as the average of prices across the supply function of a unit. Columns 1 compares the bids with the same hour of the previous day. Columns 2 compares the bids with the same hour and weekday of the previous week. Columns 3 reports whether any changes occured at the firm level.

4.3 Price Rigidities

Finally, understanding the potential role of barriers of price adjustment is very important as it can severely limit firms' ability and/or their incentives to pass-through cost changes to final prices. Recent studies have documented that nominal price rigidities can be particularly relevant at the wholesale level, which is the focus of our study. For instance, Goldberg and Hellerstein (2013) attribute 31.8% of the incomplete pass-through to the presence of repricing costs in the beer market, and Nakamura and Zerom (2010) show that menu costs explain the delayed response of coffee prices to cost shocks, even though their impact on the long-run pass-through is negligible.

Intuitively, one would expect price rigidities to be not particularly relevant in electricity markets, due to the presence of daily auctions. However, there could be costs of bid preparation that restrain firms from continuously adjusting prices. A close look at the bid data reveals that firms do not change their bids on a daily basis, but they do adjust their bids quite frequently. Table 4.4 shows that the average frequency of bid adjustment per production unit is approximately once every three days. If one were to look at changes at the company level, instead of the unit level, firms adjust at least one of their bids between 70 and 90% of the days. Taking into account that demand and supply conditions might not change vastly on a daily basis, we interpret this number as being high. The frequency of bid adjustment is even larger for Mondays and Saturdays, the two days in which, intuitively, the value of adjusting would appear to be the highest because of weekend-weekday demand variation. It thus seems that, while present, price rigidities in wholesale electricity markets are much weaker than in other sectors.[38]

[38] For instance, for the coffee industry, Nakamura and Zerom (2010) report 1.3 price changes over an 8 year period; for the beer industry, Goldberg and Hellerstein (2013) report prices remaining constant during several weeks in a row before they jump to a new level; and for the transport equipment sector, Goldberg and Hellerstein (2009) report that

5 Conclusions

We have presented an empirical assessment of the introduction of emissions regulation in the Spanish electricity market. Overall, we find that the power companies in our data appear to have responded very closely to changes in emissions permit prices. This led to an almost complete pass-through of emissions costs to electricity prices.

In order to explain why the pass-through in this market is so high, we have explored whether and why the channels that lead to partial pass-through in other settings are not present in electricity markets. For this purpose, the richness of our micro-level data has allowed us to perform a structural estimation without strong assumptions on the shape of the demand and supply curves. It has also enabled us to accurately measure firms' opportunity costs, as well as to observe emissions costs separately from other cost components.

The analysis reveals that the high measured pass-through is explained by (i) weak incentives for markup adjustment, which is in turn explained by the high correlation of cost shocks among firms and by the limited demand elasticity, and (ii) the absence of relevant price rigidities. The only instances in which we measure incomplete pass-through appear to arise due to the presence of dynamic costs, which make firms less likely to price in cost changes at night.

From a policy perspective, the finding that firms fully internalize the costs of permits suggests that auctioning permits should have no inflationary effect on electricity prices, at least in the short run. The extent of pass-through reported here also demonstrates that electricity producers benefited from windfall profits due to both free permit allocation and increased market prices, which specially benefited nuclear and hydro power plants. Indeed, the large windfall profits obtained by electricity producers in Europe generated great discomfort, and some countries decided to claw back part of these gains. In our setting, the Spanish government taxed these windfall profits ex-post, which derived into a lengthy contentious trial.[39] Given that our findings are consistent with what economic theory would predict, an important lesson is that market interventions should take into account their distributional effects and, if problematic, address them ex-ante through good market design.

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the average duration of a price change is roughly one month.

[39]In October 2013, the European Union's Court of Justice has ruled that the claw-back did not violate European Law.

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A Additional Tables and Figures

Table A.1: First Stage for Marginal Emissions Costs

	(1)	(2)	(3)	(4)	(5)
Emissions Price	0.588	0.577	0.581	0.570	0.570
	(0.053)	(0.054)	(0.051)	(0.052)	(0.052)
Temperature	0.040		0.042		
	(0.024)		(0.024)		
Maximum Temperature	-0.029		-0.030		
	(0.019)		(0.019)		
Wind Speed	0.053	-0.052	0.035	-0.060	-0.060
	(0.142)	(0.152)	(0.140)	(0.149)	(0.149)
Wind Speed Squared	0.001	0.008	0.002	0.009	0.009
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
Coal	-1.296	-3.102	-1.317	-3.156	
	(1.281)	(1.568)	(1.295)	(1.569)	
Gas	-0.368	-0.354	-0.381	-0.364	
	(0.089)	(0.096)	(0.087)	(0.094)	
Brent	0.774	0.878	0.760	0.830	
	(0.361)	(0.401)	(0.356)	(0.395)	
MonthXTemp,MaxTemp	N	Y	N	Y	Y
MonthXHour FE	N	N	Y	Y	Y
HourXInput	N	N	N	N	Y

Notes: Sample from January 2004 to February 2006, includes all thermal units in the Spanish electricity market. All specifications include month of sample, weekday, and hour fixed effects, as well as weather and demand controls (temperature, maximum temperature, humidity), supply controls (wind speed and wind speed squared); and common controls (commodity prices of coal, gas, and oil). Robust standard errors in parentheses. Number of observations: $16,186$.

Table A.2: Cost Pass-through Regression - Additional controls

	(1)	(2)	(3)	(4)
Mg. Emissions Costs (ρ)	0.848	0.890	0.876	0.870
	(0.168)	(0.178)	(0.179)	(0.178)
Wind Speed	-2.238	-2.226	-2.194	-1.320
	(0.329)	(0.332)	(0.333)	(0.352)
Wind Speed Squared	0.068	0.065	0.063	0.060
	(0.023)	(0.023)	(0.023)	(0.023)
Wind Speed X Trend				-0.918
				(0.111)
F-test	118.3	104.5	102.3	102.8
Quadratic Inputs	N	Y	Y	Y
Temperature Squared	N	N	Y	Y
Wind Speed Trend	N	N	Y	Y

Notes: Sample from January 2004 to February 2006, includes all thermal units in the Spanish electricity market. All specifications include month of sample, weekday, and hour fixed effects, as well as weather and demand controls (temperature, maximum temperature, humidity), supply controls (wind speed and wind speed squared); and common controls (commodity prices of coal, gas, and oil). The marginal emissions cost is instrumented with the emissions price. Robust standard errors in parentheses. Number of observations: $16,186$.

Table A.3: Cost Pass-through Regression Results for different Emissions Assumptions

	(1)	(2)	(3)	(4)	(5)
Interpolated Emissions Costs	0.894	0.917	0.894	0.917	0.917
Obs. = 18,744	(0.181)	(0.184)	(0.163)	(0.164)	(0.156)
Mg. Emissions Costs					
(Units & Technologies)	0.862	0.860	0.835	0.829	0.848
Obs. = 16,186	(0.181)	(0.182)	(0.173)	(0.172)	(0.168)
Mg. Emissions Costs					
(Units Only)	0.861	0.806	0.901	0.799	0.802
Obs. = 14,928	(0.178)	(0.176)	(0.067)	(0.172)	(0.167)
MonthXTemp,MaxTemp	N	Y	N	Y	Y
MonthXHour FE	N	N	Y	Y	Y
HourXInput	N	N	N	N	Y

Notes: Sample from January 2004 to February 2006, includes all thermal units in the Spanish electricity market. All specifications include month of sample, weekday, and hour fixed effects, as well as weather and demand controls (temperature, maximum temperature, humidity), supply controls (wind speed and wind speed squared); and common controls (commodity prices of coal, gas, and oil). The marginal emissions cost is instrumented with the emissions price. Robust standard errors in parentheses.

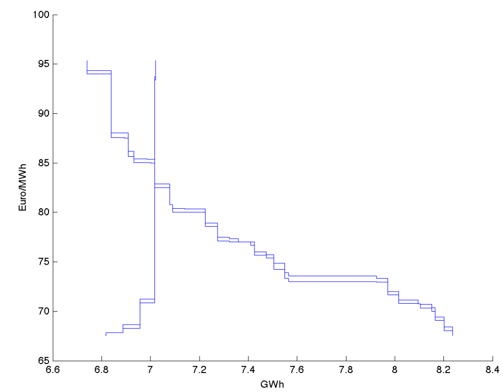
Table A.4: Test based on structural equations – Effects of Clustering

	All	Firm 1	Firm 2	Firm 3	Firm 4
Emissions cost (γ)	0.971	0.947	0.963	1.062	0.803
(1) Unit-Level Clusters	(0.034)	(0.031)	(0.039)	(0.046)	(0.102)
(2) Robust Std. Errors	(0.010)	(0.012)	(0.013)	(0.024)	(0.022)
(3) Firm-Day Clusters	(0.019)	(0.023)	(0.021)	(0.045)	(0.029)
(4) Firm-Month Clusters	(0.039)	(0.061)	(0.064)	(0.081)	(0.082)
Input cost (β)	0.598	0.494	0.303	0.821	0.643
(1) Unit-Level Clusters	(0.064)	(0.057)	(0.055)	(0.037)	(0.053)
(2) Robust Std. Errors	(0.022)	(0.027)	(0.028)	(0.036)	(0.115)
(3) Firm-Day Clusters	(0.037)	(0.039)	(0.041)	(0.058)	(0.235)
(4) Firm-Month Clusters	(0.062)	(0.054)	(0.080)	(0.103)	(0.259)
Obs.	9,257	3,029	1,988	2,805	1,435

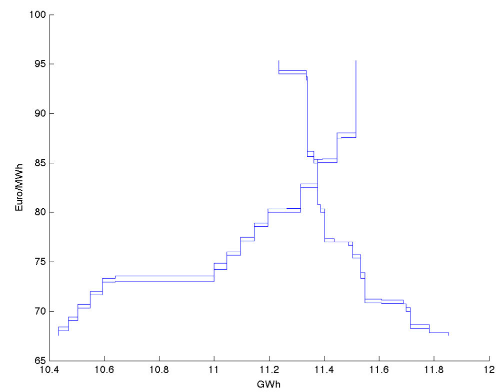
Notes: Sample from January 2004 to February 2006, includes all thermal units in the Spanish electricity market. Regression includes unit fixed effects. Each row considers a different level of clustering: unit-level clusters (our baseline specification), robsut White standard errors, firm-day clusters to account for correlation in bidding within a firm at a given day, and firm-month of sample clusters to account for longer temporal clustering.

Figure A.1: Example of Strategy Perturbations

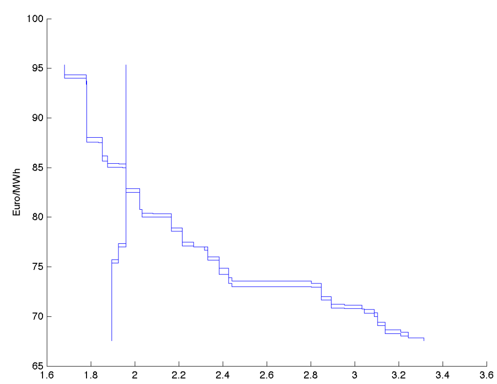
(a) Strategy Perturbations for Firm 1



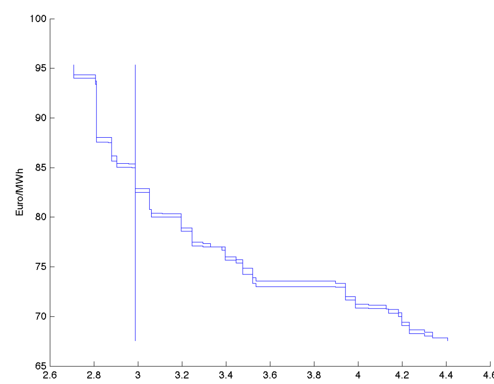
(b) Strategy Perturbations for Firm 2



(c) Strategy Perturbations for Firm 3



(d) Strategy Perturbations for Firm 4



Notes: Figures depict the shift in supply and inverse residual demand curves as a result of an increase in the carbon price by one euro. For better comparison, the same day and hour is used for all firms.