

Opportunity Costs and Pass-through of Emission Costs*

Natalia Fabra
U. Carlos III de Madrid

Mar Reguant
Stanford GSB and NBER

A. Jesús Sánchez-Fuentes
U. Complutense de Madrid

September 21, 2012

VERY PRELIMINARY AND INCOMPLETE
Please, do not cite or circulate

Abstract

We analyze the response of firms to the introduction of emissions permits in the Spanish electricity market. While previous papers have focused on assessing the pass-through of emission costs to electricity prices, there is still little evidence on how firms incorporate these costs in their output or pricing decisions. If there are significant frictions in the market, the emissions price might not be reflective of the opportunity cost of the permits, which could bias pass-through estimates. We proceed in two steps. First, we hypothesize and test that the emissions market price is the opportunity costs perceived by the firms. Second, we decompose the other channels that might affect the pass-through, such as demand response, market power and heterogeneity of cost shocks. Results are consistent with the price of the emissions as being reflective of the opportunity cost of the free permits. We also find incomplete pass-through of emission costs and pass-through distributions consistent with cleaner generators substituting dirtier ones at the margin.

Keywords: Cost internalization, pass-through, emission permits, electricity markets.

JEL classification: L13, L94, D44.

*We are grateful to José-Antonio Espín, Joe Harrington and Michael Waterson for helpful comments on earlier versions. We also want to thank seminar audiences at CEMFI (Madrid), EARIE Conference (Rome), Jornadas de Economía Industrial (Murcia), Vth Atlantic Conference (La Toja), University of Arizona (Tucson), the Berkeley-Stanford IO Fest and University Carlos III (Madrid). E-mails: natalia.fabra@uc3m.es, mreguant@stanford.edu, antoniojesus.sanchez@ccee.ucm.es.

1 Introduction

Understanding how firms respond to the introduction of cap-and-trade regulation and how this affects the product market is of great importance to assess the benefits of these programs. One of the main benefits of using cap-and-trade for pollution abatement, as opposed to command-and-control methods, is that the former ensure that, in the absence of any other distortions, the lowest abatement cost allocation will be achieved.

To achieve the least cost allocation, it is required, among other assumptions, that firms internalize the costs of the emissions accordingly. Regardless of whether firms receive the permits for free or not, the relevant cost that producers internalize when taking their pricing or output decisions is the opportunity cost of using those permits. In a frictionless emissions markets, the opportunity cost of permits is given by their market price. However, potential market distortions could open a wedge between the true opportunity costs that firms internalize and the market price for those permits. Market distortions might arise because of transaction costs, the threat of regulatory intervention, the belief that future permit allocations will be based on current emissions, or because of firms' behavioral biases. The question of whether firms' perceived opportunity costs fully reflect the market price of permits has not been explored extensively in an empirical setting.

One of the issues that has confounded the debate on the effects of pollution permits on firms' decisions has been the belief that in competitive markets full internalization of the price of the permits is necessarily associated with a full pass-through.¹ Therefore, evidence on partial pass-through has at times been interpreted as either evidence of firms not perceiving the price of the emissions as their opportunity cost or evidence of firms exercising market power. Even though this statement is true in some theoretical models, it does not hold generally.

The goal of the paper is to separately quantify these two important economic concepts (opportunity cost and pass-through of emission costs) in the context of electricity markets. Whereas the opportunity cost relates to the degree to which firms incorporate the price of emissions into their supplying behavior, the pass-through rate is concerned about how this opportunity cost translates into higher equilibrium prices.

To address these issues, we examine the response of generators in the Spanish electricity market to the introduction of the European Union Emissions Trading Scheme (EU ETS), a cap-and-trade program regulating CO₂ emissions from energy intensive sectors. Studying the pass-through rates in the context of the EU ETS and electricity markets presents several advantages. From a policy point of view, the electricity sector is currently the largest CO₂ contributor in the European Union.² Furthermore, the effects of CO₂ permit prices on the marginal costs of generating electricity are significant and vary by technology. This creates important interactions that affect the degree of abatement in this market (e.g. through the increase in the production of cleaner technologies at the expense of dirtier ones) and makes the potential impacts of the policy important.

¹See [Ellerman et al. \(2010\)](#) for a discussion.

²In compliance with the EU's Energy Roadmap 2050, it is expected that the sector will have to almost fully eliminate its CO₂ emissions by 2050.

From an econometric perspective, analyzing the effect of emission costs in electricity markets has the advantage that European CO₂ prices can be considered exogenous cost shifters, as they are traded across all Member States and across many sectors. Furthermore, there is substantial variation in permit prices during the sample. Electricity markets are also particularly suited for this analysis. First, there is rich micro-level data, including demand and supply curves that allow us to be flexible in the estimation.³ The availability of detailed engineering-based cost estimates also allows us to confront results from models that estimate those costs either directly or indirectly. Furthermore, the institutions and industrial processes that affect firms' strategic behavior in these markets are well understood.⁴

We examine the hypothesis that the opportunity cost of the permits is the emissions market price using two tests that rely on different assumptions. First, we construct structural form estimates using predictions of optimal bidding from the multi-unit auction literature. Second, following [Reguant and Ellerman \(2008\)](#), we derive a test of internalization which relies on predictions related to firms' incentives to turn on or off a particular power plant on a given day.

We then examine the pass-through of emission costs. We quantify the pass-through rate through a structural approach based on auction-level data, and a reduced-form approach based on observed equilibrium prices and quantities. Overall, we focus on demand elasticity, market power and heterogeneity in cost shocks as the main factors explaining the observed distribution of pass-through rates.

We find evidence that Spanish electricity firms fully internalized the price of emissions rights. Based on results of both reduced-form and structural models, one cannot reject that the market price reflects the opportunity cost of the permits. This translated into a 50% price increase, due to a combination of heterogeneous cost shocks and substitution effects across technologies. In contrast, the cost pass-through is close to 100%.

This evidence has several policy-relevant conclusions. First, during the sample period, firms were given emission permits for free. In contrast, starting January 2013, full auctioning of emission permits becomes compulsory. The fact that firms internalized the full costs of free permits suggests that auctioning of those permits should not have additional inflationary effects on electricity prices, at least in the short run.⁵ Second, full cost internalization suggests that frictions or transaction costs in the emission market are negligible, which as is well known is a necessary condition for the Coase principle to apply. Last, evidence of full cost internalization also mitigates concerns over distortions created by the allocation method: if firms had expected that future permit allocations would increase with current emissions, they would have tended to over-produce, but this would have led to partial rather than to full internalization of emission costs.

The contributions of the paper are twofold. First, this is one of the first papers to present strong

³This is particularly important for the estimation of pass-through rates, which can be greatly affected by functional form assumptions ([Besanko et al., 2005](#); [Weyl and Fabinger, 2012](#)).

⁴For seminal works on the study of strategic behavior in electricity markets, see [von der Fehr and Harbord \(1993\)](#) and [Green and Newbery \(1992\)](#).

⁵This conclusion has been corroborated in the lab; see [Goeree et al. \(2010\)](#).

firm-level empirical evidence supporting the hypothesis of full cost internalization in the presence of pollution permits (Reguant and Ellerman, 2008; Fowlie, 2010). Second, this is the first paper to quantify pass-through rates in the EU ETS market using micro-level data. More broadly, the paper contributes to the understanding of both cost internalization and pass-through by taking advantage of the presence of cost shocks due to the introduction of pollution permits.

The paper proceeds as follows. After reviewing the related literature, section 2 describes a conceptual framework to define the terms of cost internalization and pass-through rates. We then introduce the context and data of analysis in section 3. In section 4, we present the empirical strategy to identify the degree of cost internalization and the empirical results. In section 5, we identify and quantify of the pass-through, while section 6 concludes.

Related literature This paper is related to the literature on the effects of environmental policies on firms' decisions. It is closely related to the work by Reguant and Ellerman (2008), which also presents evidence on firms internalizing the costs of the emissions in the Spanish electricity market. McGuinness and Ellerman (2008) present evidence that electric utilities in the UK changed their operational decisions in response to carbon prices in the EU ETS, although they do not directly assess whether the response is consistent with full internalization.

In the context of other pollution markets, Kolstad and Wolak (2008) present evidence on how firms used NO_x prices to strategically exercise market power in the Californian electricity market. In their study, they test for cost internalization using structural equations from the multi-unit auction literature, as in this paper. They find evidence supporting the hypothesis that firms respond differently to environmental cost shocks, as opposed to other marginal cost shocks. Fowlie (2010) examines firm responses in the context of the NO_x Budget Program, exploiting the differences in allocation regimes. She finds suggestive evidence that firms internalized the costs of emissions, and that the degree of internalization depended on the subsidization rate, as theory would predict. Results of experiments in the lab (Goeree et al. (2010) and Wrake et al. (2010)) also confirm that, after some initial rounds of learning, agents understand that the opportunity of costs of free permits has to be internalized, so that their behavior converges to that predicted by the theory.

Regarding the pass-through analysis, this paper is related to previous papers that have examined pass-through rates in the context of the EU ETS. For example, Sijm et al. (2006) estimate pass-through rates using equilibrium prices and fuel cost data in the German electricity market.⁶ They find pass-through rates that range between 0.60 and 1.17, depending on market conditions. Bushnell et al. (2011) use a structural break that occurred in April 2006 in the EU ETS prices to measure the pass-through rate, and Zachmann and Hirschhausen (2008) document whether it responds asymmetrically to either positive or negative cost shocks. Whereas previous studies on pass-through rates are based on market outcomes, this paper has the advantage of using finer micro-level data to assess the response by firms more directly.

The relevance of identifying the pass-through rate in the presence of cost shocks extends beyond

⁶See the Annex by Keppler in Ellerman et al. (2010) for a review of this and other studies.

emission markets, and has indeed been the subject of a more general literature. From a theoretical perspective, the effects of cost changes on prices cannot be determined, as discussed in [Besanko et al. \(2005\)](#) and [Weyl and Fabinger \(2012\)](#). Empirically, several settings have been examined to answer this question. A big part of the literature has exploited changes in currency exchange rates to examine the relevance of pass-through, as they can provide exogenous variation in costs ([Goldberg and Hellerstein, 2008](#)). Some papers have focused on the incidence of taxes, also as a way to measure the effects of observable cost changes. For instance, exploiting the variation in gasoline taxes, [Marion and Muehlegger \(2011\)](#) provide evidence of full pass-through in the gasoline retail market.⁷ [Bonnet et al. \(2012\)](#) have analyzed the incidence of vertical contracts on pass-through rates using a structural model. As noted by [Weyl and Fabinger \(2012\)](#), “broader empirical work on the range of pass-through rates and their relationship to more-easily-observable industry features remains extremely limited.” This work contributes to this line of research.

2 Opportunity costs and pass-through

In this paper, we separately identify the opportunity cost CO₂ emission permits and the pass-through rates of such costs in the context of the Spanish electricity market.

Consider a simple model in which a single firm is facing demand $D(p; \epsilon)$, where p is the market price and ϵ is a demand shock. The firm has costs $C(Q; u)$, where Q is quantity and is u a cost shock. The firm also faces environmental costs $e\tau Q$, where e is the emissions rate and τ is the emissions permit price.⁸

Consider a situation in which the perceived costs by the firm are given by

$$TC(Q; \gamma) = C(Q; u) + \gamma e\tau Q.$$

In this context, γ represents how the firm perceives the cost of emissions. The common assumption is that the price of the emissions τ fully reflects the cost of the emissions, i.e., $\gamma = 1$. However, in the case of emissions programs, there exists some policy debate on how firms actually treat these costs in practice. Several reasons have been suggested to explain why firms could potentially internalize only a fraction of emissions costs; for instance, firms’ difficulty in understanding that emission costs entail an opportunity cost despite the fact that they were handed in for free, the existence of transaction costs even when firms recognize that permits can be traded, the threat of regulatory intervention if electricity prices increase too much due to the internalized emission costs,⁹ or the belief that future permit allocations will be increasing in current emissions.

⁷[Besanko et al. \(2001\)](#) and [Besanko et al. \(2005\)](#) measure individual-firm pass-through rates for firms selling differentiated products. In our set-up, there is a single pass-through rate since electricity is an homogeneous product, and therefore there is a single market price.

⁸For the sake of simplicity, in this example we assume that the emission rate is constant in output. However, note that in reality, this need not be the case given that different technologies have different emission rates.

⁹For instance, in 2006 the German antitrust authority sent a warning letter to one of the main electricity producers stating that the prices charged to industrial consumers were abusive because the firm had passed-through more than 25% of CO₂ prices. Similar episodes occurred in Belgium and in the UK. See [Wrake et al. \(2010\)](#) for details.

Whereas the perceived opportunity costs, captured by γ , is a fundamental parameter of the model, the pass-through rate is an equilibrium outcome. Consider the equilibrium supply as $S(p, \tau; u, \gamma)$. Using the market clearing condition, $D(p; \epsilon) = S(p, \tau; u, \gamma)$, by the implicit function theorem the pass-through rate can be expressed as

$$\rho \equiv \frac{dp}{d\tau} = \frac{S_\tau(p, \tau; u, \gamma)}{D_p(p; \epsilon) - S_p(p, \tau; u, \gamma)}. \quad (2.1)$$

It is important to note that this pass-through does not generally equal one, even in the presence of competitive firms. However, under specific circumstances, $\rho = 1$. For instance, full pass-through is achieved in competitive markets with inelastic demand. In this case, a firm changes its supply curve one to one with the increase in costs (given that $p = C'(Q) + e\tau$, $S_\tau(p, \tau; u, \gamma) = -S_p(p, \tau; u, \gamma)$), and demand remains the same ($D_p(p) = 0$), so that the cost increase is fully passed-through to market prices. Full pass-through is also achieved in competitive markets with perfectly elastic supply, i.e., when marginal costs are flat.¹⁰

There is a common misconception that an incomplete pass-through goes hand in hand with either market power or lack of cost internalization. Yet, it could also be consistent with competitive behavior and full cost internalization under downward-sloping demand and upward-sloping supply. In general, an incomplete pass-through can arise both in competitive markets or in the presence of market power even under full internalization; it can also arise because the emissions price does not reflect the true opportunity cost, whether there is market power or not. This is shown graphically in Figure 2.1 in the form of three different examples.

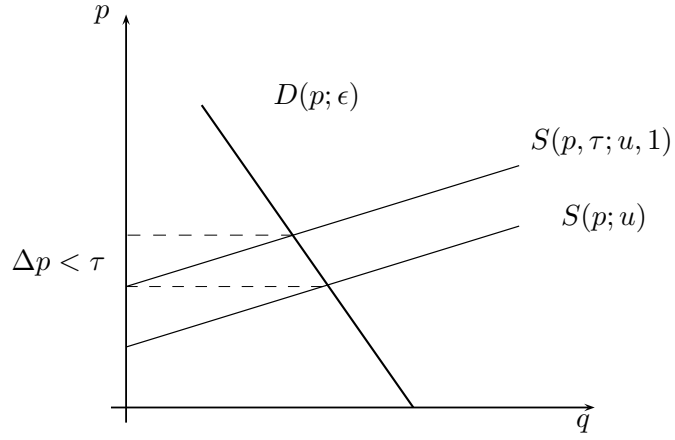
Example (a) represents the case in which firms are competitive and they have linearly increasing marginal cost. As long as demand is elastic, the pass-through is less than one. Example (b) represents the case in which firms exercise market power. In the example, firms have constant marginal cost but, consistent with many oligopoly models including Cournot or the multi-unit auction setting, they increase their markup as they produce more q . Because the effective supply curve is elastic, this is equivalent to example (a). Example (c) represents the case in which firms the emissions price does not reflect the opportunity cost of the emissions. Because marginal costs are constant, one should observe a full pass-through in a competitive equilibrium. However, since there is partial cost internalization, consumers only face part of the cost increase. In this case, if we wrongly assumed full internalization, we would be underestimating the pass-through rate. In general, the actual observed pass-through is potentially a combination of these different factors: the elasticity of supply and demand, the degree of market power, and the relevant opportunity costs.

As the previous discussion shows, to separately identify the different hypothesis for explaining the observed pass-through in these markets, it is important to first design a test for cost internalization. It is important to note that the test for cost internalization is a test on the supply curve only, whereas the identification of the channels through which the pass-through is determined involves

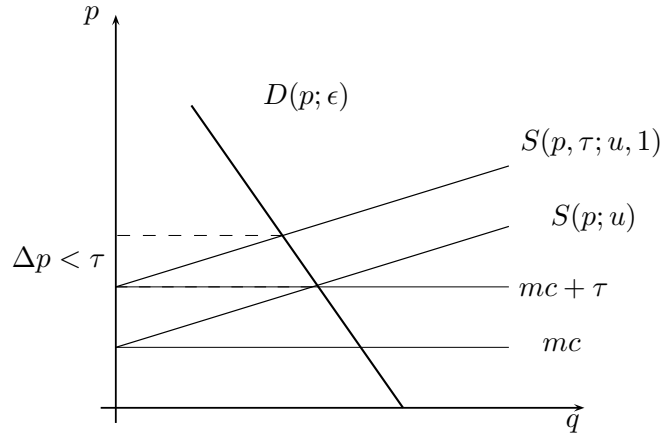
¹⁰In this case, ρ in equation (2.1) is undefined as $S_\tau(p, \tau; u, \gamma) = -S_p(p, \tau; u, \gamma) \rightarrow \infty$. To solve this indeterminacy, let's parametrize costs as $C(Q) = Q^\alpha$. Now, as $\alpha \rightarrow 1$, so that marginal costs become constant, $S_{\tau\alpha} = -S_{p\alpha}$ and $D_{p\alpha} = 0$, so that $\rho \rightarrow 1$.

Figure 2.1: An incomplete pass-through is consistent with several hypothesis

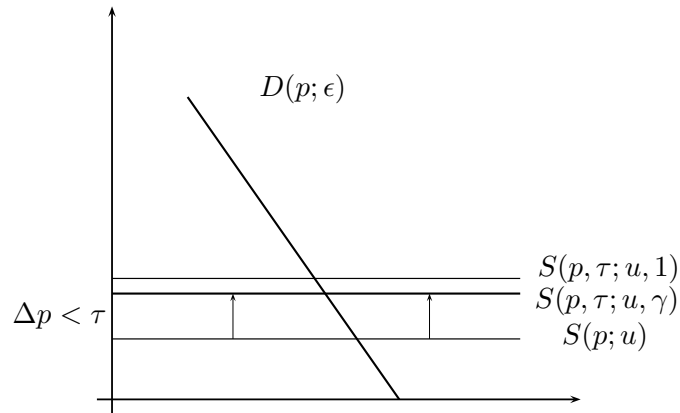
(a) An incomplete pass-through is consistent with competitive behavior when both demand and supply are elastic



(b) An incomplete pass-through is consistent with market power



(c) An incomplete pass-through is consistent with partial internalization of emissions costs



both demand and supply.

3 Context and data

We study the decisions of electricity generators in the Spanish market following the introduction of carbon permits. The electricity sector is one of the sectors most affected by the European Union Emissions Trading Scheme (EU ETS), and it is therefore well-suited for this analysis. Furthermore, the fact that generation decisions are made very frequently allows us to exploit the variation of marginal costs due to changing carbon prices at a fine level. We briefly describe the context of our analysis as well as the data that we use for the empirical analysis.

3.1 The European Union Emissions Trading Scheme

The EU ETS is the largest emissions control scheme in the world, affecting almost half of European CO₂ emissions, from approximately 10,000 energy-intensive installations across the EU. It is also the first compulsory international trading system for CO₂ emissions.¹¹

The system works as follows. The EU sets a global cap on emissions and assigns a share of free permits to each member state. Through the National Allocation Plans, Member States then allocate their share of permits across sector and individual installations subject to EU approval.¹² At the end of each year, each company must surrender enough allowances to cover the emissions of all its installations. To comply, firms can either submit their own allowances or freely trade them across Member States; failure to comply implies a €40/t CO₂ penalty, plus the obligation to purchase the deficit in the market. Emission rights can be transacted bilaterally (i.e. company-to-company), brokered (OTC market) or traded in exchanges.¹³

The first phase of the EU ETS, also known as the trial period, ran from January 2005 to December 2007. Phase I 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 CO₂ emissions in the European Union, the electricity sector being the largest contributor in the group.¹⁴

Figure 3.1 shows the evolution of CO₂ prices during the trial period. One of the striking features is the substantial drop in prices around May 2006. This drop in price was induced by the release of emissions reporting data from 2005, the first year of the policy. In light of the

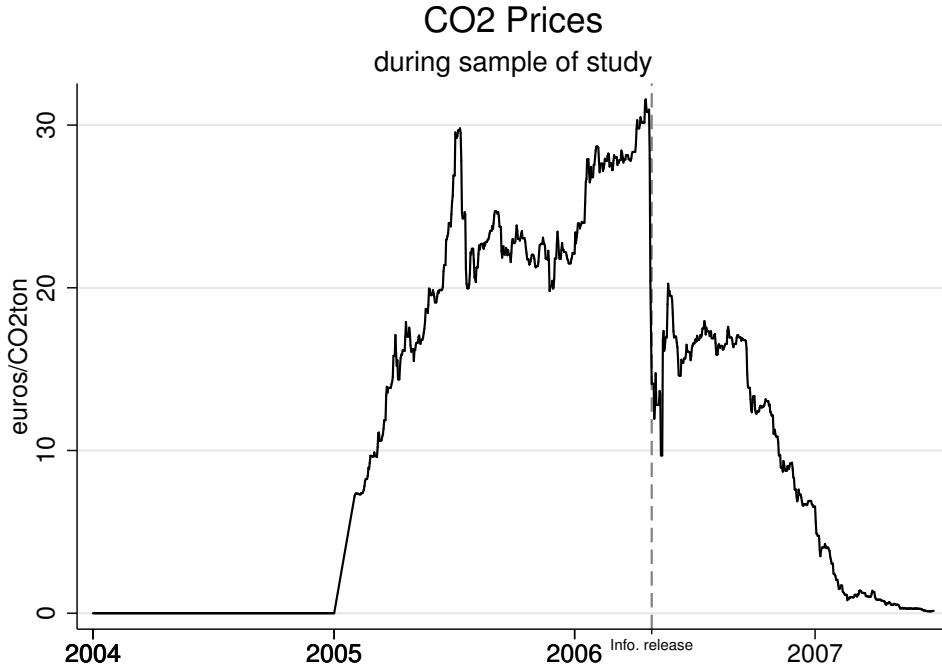
¹¹A non-mandatory precursor of the EU ETS is the Chicago Climate Exchange, which was a voluntary greenhouse gas (GHG) reduction and trading system.

¹²For details regarding the allocation of allowances in each Member State see [Ellerman et al. \(2007\)](#).

¹³To get some orders of magnitude, in 2005, the market transacted 262 Mt CO₂ (€5.4 billion) through brokers (207 Mt) and exchanges (57 Mt), and an estimated figure of 100Mt (€1.8 billion) in the bilateral market (Point Carbon 2006). European Climate Exchange is the largest exchange in Europe (63%), followed by NordPool (24%), PowerNext (8%) and the European Energy Exchange (4%).

¹⁴For more details on the EU ETS, see [Ellerman et al. \(2007\)](#) and [Bahringer and Lange \(2012\)](#).

Figure 3.1: Evolution of EUA prices during the EU ETS trial period



revealed information, which indicated a markedly lower level of emissions than had originally been anticipated and therefore a lower marginal cost of meeting the cap, the price halved in a very short period of time and subsequently declined to zero (Parsons et al., 2009). Even though we do not explicitly exploit this drop in prices, it will contribute to the variation in CO₂ prices that will help identify the internalization and pass-through of emissions costs.¹⁵

3.2 The Spanish electricity market

The Spanish electricity market is a national market that produces between 15,000 and 45,000 MWh hourly, has around 85,000 MW of installed capacity, and serves more than 40 million people.¹⁶ The Spanish territory is interconnected with France, Morocco and Portugal. The electricity market has an annual value of 6 to 8 B€.

The Spanish electricity market has been liberalized since 1998 and shares many features with other liberalized electricity markets. More specifically, it operates in a sequence of markets: the day-ahead market, several intra-day markets that operate close to real time, and the ancillary services market.¹⁷ Participation in these markets is not compulsory, as market participants are

¹⁵Bushnell et al. (2009) and Zachmann and Hirschhausen (2008) explicitly exploit this change to analyze the response of firms to changing market conditions.

¹⁶Compared to liberalized electricity markets in the United States, the Spanish electricity market has a size comparable to the Californian electricity market.

¹⁷The Spanish electricity market has gone through several reforms since its inception in 1998. For the sake of clarity, we only describe here its main features during our sample period.

allowed to enter into physical bilateral contracts. Still, the day-ahead market is very liquid and concentrates the vast majority of trades.

The day-ahead market trades 24 hourly electricity products that are cleared once a day. On the supply side, electricity producers, if not tied to a bilateral contract, submit supply functions specifying the minimum price at which they are willing to produce a given amount of output. On the demand side, distributors, independent retailers and large consumers submit demand functions specifying the maximum price at which they are willing to purchase a given amount of electricity. The market operator constructs a merit order dispatch by ordering the supply and demand bids in ascending and descending order, respectively. By intersecting both curves, it determines the winning bids and the market clearing price, which is paid to all dispatched units from the supply side, and paid by all the accepted units from the demand side.

Once the day-ahead market closes, the System Operator studies the feasibility of the dispatch and modifies it by adding or removing the energy required to solve local congestion. The System Operator also runs several markets in which production units compete to commit their capacity to provide ancillary services when needed. Following these procedures, market participants may adjust their positions in either direction in a sequence of six intra-day markets.

During our sample period, electricity was essentially produced by four vertically integrated incumbent firms. The generation mix was made of nuclear, coal, CCGTs, oil-gas, hydro power, and renewable resources, of which wind was the most important. Table 3.1 provides information on the production by each technology type during the sample period.

The regulatory framework of the Spanish electricity market was rather stable during our sample period, with one notable exception. In March 2006, the government passed the Royal Decree 3/2006, which 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. As this might have had an effect on firms' strategic behavior, we remove the dates during which this Royal Decree was in place in some specifications.

3.3 The data

To perform the empirical analysis, we construct a data set that contains supply functions submitted on a hourly basis by the Spanish electricity producers from January 2004 to June 2007.¹⁸ This data set also contains both MWh produced at the plant level on an hourly basis, as well as unit available capacity net of forced outages and planned shut downs. We also collect characteristics at the unit level: maximum available capacity, type of fuel used, vintage, generating company, geographic location, etc. We combine these data with other market outcomes, such as the hourly day-ahead and final average electricity prices, and aggregate output by types of technology. We also use publicly available information on CO₂ allowance prices (EUA prices), as well as coal, gas,

¹⁸Data are publicly available at the system and market operator web sites, www.esios.ree.es and www.omel.es. The Spanish and the Portuguese electricity markets merged in July 2007. As this had a significant impact on market behavior, we have decided to truncate the data set at that date.

Table 3.1: Production Mix in Spain, 2004-2007

	2004	2005	2006	2007
Capacity (MW)	68,758	74,123	79,203	85,698
Coal	11,565	11,424	11,424	11,357
CCGT	8,233	12,224	15,500	20,958
Trad. oil/gas	6,947	6,647	6,647	4,810
Nuclear	7,876	7,876	7,716	7,716
Trad. Hydro	13,930	13,930	13,930	13,930
Renewable	10,984	12,633	14,465	17,329
Others	6,495	6,661	6,794	6,871
Gross annual production (GWh)	252,280	262,966	270,890	280,125
Coal	76,358	77,393	66,006	71,833
CCGT	28,974	48,885	63,506	68,139
Trad. oil/gas	7,697	10,013	5,905	2,397
Nuclear	63,606	57,539	60,126	55,102
Trad. Hydro	29,777	19,169	25,330	26,352
Renewable	23,387	28,142	30,782	35,729
Others	22,482	21,824	19,236	20,574

Notes: Data from Annual Report of the System Operator (2004-2007). Only generation in inland territories is included.

and oil prices in international markets.

We also have reliable information on efficiency rates at the plant level (i.e., the rates at which each plant converts the heat content of the fuel into output).¹⁹ Using similar techniques as [Wolfram \(1999\)](#) and [Borenstein et al. \(2002\)](#), this information allows us to estimate the short-run marginal costs of thermal plants, which also depend on the type of fuel each plant burns, the cost of the fuel (as set in international input markets),²⁰ and the short-run variable cost of operating and maintaining the plant (O&M).

We have also collected annual information on CO₂ emissions at the plant level from the National Register, for the years 2001-2004. These data are merged with the emissions data during the EU-ETS trial period 2005-2007. We have estimated emissions rates at the plant level for each year, by dividing total emissions by total output at the annual level. Emissions rates do not fluctuate much at the unit level and are consistent with typical fuel benchmark emissions for the generation plants involved. Therefore, they are strongly correlated across units that use the same fuel. 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 1.00 to 1.10 tons/MWh. Natural gas

¹⁹This 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). This data are also used in [Fabra and Toro \(2005\)](#).

²⁰For coal units, we use the MCIS Index, for fuel units we use the F.O.1% CIF NWE prices, and for gas units we use the Gazexport-Ruhr gas prices. All series are in c€/te. We have downloaded this information from Bloomberg.

Table 3.2: Summary statistics of power generators

	Coal	Gas	Peaking	Total
Total number of units	36	38	15	89
Relative number of units (%)	41.1	41.6	17.3	100
Average vintage (year built)	1977	2005	1971	1989
Average capacity of units (MW)	314	472	346	383
Average capacity factor (MWh/MW)	0.65	0.37	0.07	0.43
Average emissions rate (tons/MWh)	0.95	0.35	0.72	0.65

Notes: Sample from 2004 to 2007, including all thermal units (except nuclear power plants) in the Spanish electricity market that are active at some point during the period.

generators tend to have an emissions rate around 0.35 tons/MWh.

Table 3.2 summarizes the characteristics of power plants in the Spanish electricity market. There are around 90 thermal units that are subject to emissions control. The units can be broadly categorized in three different categories, depending on the fuel they use. Coal units are thermal plants that use coal as their main fuel. In Spain, these plants typically use a combination of national coal and imported coal. Depending on their inputs, they will have different emissions rates, which average 0.95 tons/MWh. Combined cycle natural gas units (CCGTs) are of new construction and have much lower emissions rates, averaging 0.35 tons/MWh. Since the marginal costs of CCGTs are higher than those of coal units, they tend to be used less frequently. However, because of their different emission rates, a high enough price of CO₂ emission permits might reverse the ranking of these two technologies in favor of CCGTs. Finally, peaking plants are oil-fired or gas-fired plants that are more inefficient than newer gas plants and tend to operate very infrequently. One can see that these plants are very old, with an average vintage of 1971, and a capacity factor only around 7% over the sample from 2002 to 2007.²¹

Table 3.3 summarizes the generation mix of the four major firms in the market that we will be analyzing. These four firms own 59 of the 89 power generators affected by the cap-and-trade mechanism, as well as most hydro and nuclear generators and part of the renewable resources. The two largest firms have a over 6,000MW of installed thermal capacity. The composition of the mix across firms is somewhat different: while firm 1 is more focused on coal and oil, firm 2 has a larger presence in the CCGT segment, which makes it the most efficient firm in terms of emissions costs.

4 Evidence on Opportunity Costs

Identifying the value of the opportunity costs is a necessary condition for quantifying the pass-through rate. Hence, we first discuss the empirical strategy and results regarding the internalization

²¹The capacity factor expresses how much a unit is utilized with regards to its full potential, and therefore can be expressed as the average output of a unit (MWh) divided by its maximum capacity (MW).

Table 3.3: Characteristics thermal plants of the 4 main firms

	Firm 1	Firm 2	Firm 3	Firm 4
Avg. number of units	23	18	12	6
Avg. unit capacity (MW)	359.78	378.08	307.75	327.85
Avg. Vintage	1980	1980	1983	1979
Avg. emissions rate	0.79	0.70	0.82	0.88
Total capacity (MW)	8,220	6,683	3,754	1,967
Coal capacity (%)	64.4	18.2	55.6	80.1
CCGT capacity (%)	15.3	41.0	43.0	19.9
Oil/gas capacity (%)	20.3	39.8	12.4	0.0
Avg. hourly production (MWh)	3958.09	3234.51	1331.22	542.75

Notes: Sample from 2004 to 2007, including all thermal units (except nuclear power plants) in the Spanish electricity market that are active at some point during the period.

of emissions costs. We use two models that complement each other: we first present a test of cost internalization using a structural model of optimal bidding; we then measure cost internalization based on daily participation decisions.

4.1 Test based on structural bidding equations

We start by estimating the degree of cost internalization by explicitly modeling strategic bidding behavior, as predicted by the multi-unit auctions literature. More specifically, under the assumption of profit-maximizing behavior, we infer the degree of emission costs internalization from the bids submitted by firms in the day-ahead market.

Consider a model in which market demand is given by $D(p; \varepsilon)$. Let $S_{-i}(p; u_{-i})$ denote the aggregate supply of all firms in the market other than firm i , where p is the market price and u_{-i} is a vector of supply-side cost shocks. Then, the residual demand faced by firm i can be written as $D_i^R(p; \varepsilon, u_{-i}) = D(p; \varepsilon) - S_{-i}(p; u_{-i})$. Under market clearing, firms produce over their residual demand, so that firm i 's output is given by $Q_i^S = D_i^R(p; \varepsilon, u_{-i})$. Under the assumption that emissions costs are linear in output, firm i 's cost can be decomposed as the sum of production costs $C(Q_i^S; u_i)$ and the firm's perceived emissions costs, $\gamma_i e_i \tau Q_i^S$, where γ_i is the firm's cost perception, e_i is the emissions rate and τ is the carbon price. Last, in order to allow for the effects of vertical integration, we let Q_i^D denote the electricity that firm i has to procure in the wholesale market in order to cover its retail sales.²²

We can write firm i 's profits in the day-ahead market as follows:²³

$$\pi_i(p; \varepsilon, u) = p (D_i^R(p; \varepsilon, u_{-i}) - Q_i^D) - C(Q_i^S; u_i) - \gamma_i e_i \tau Q_i^S.$$

²²In principle, retailers are allowed to submit downward sloping demand functions. However, in practice, retailers submit vertical demand functions. The reason is that the vast majority of retail customers face fixed retail prices that are not indexed to wholesale prices. Accordingly, we assume that the retailers' purchases are independent of wholesale prices.

²³We have omitted revenues retail sales given that these are fixed and should thus not affect bidding incentives in the electricity day-ahead market.

Assuming that the profit function above is differentiable, in any equilibrium in which firm i is setting the market price, the First Order Condition (FOC) of profit maximization must be satisfied for firm i .²⁴ Solving the FOC for p ,

$$p = c(Q_i^S) + \gamma_i e_i \tau + \left| \frac{\partial D_i^R}{\partial p} \right|^{-1} (Q_i^S - Q_i^D),$$

where $c(Q_i^S)$ is the marginal production cost at Q_i^S .

Based on this optimal bidding condition, we estimate the following empirical equation in those hours in which firm i is setting the market price:

$$b_{ijth} - \left| \frac{\partial \widehat{D}_{ith}^R}{\partial p_{th}} \right|^{-1} Q_{ith} = \alpha_j + \beta c_{jt} + \gamma_i e_j \tau_t + \epsilon_{ijth}, \quad (4.1)$$

where

- b_{ijth} = marginal bid offer by firm i when setting the price with unit j , hour h and day t ,
- α_j = unit j fixed-effect,
- c_{jt} = marginal costs of marginal unit j ,
- e_j = emissions rate of the marginal unit,
- τ_t = daily cost of the CO₂ allowances,
- $\frac{\partial \widehat{D}_{ith}^R}{\partial p_{th}}$ = estimated slope of residual demand curve at the margin,
- Q_{ith} = inframarginal quantity for firm i at the margin,
- ϵ_{ijth} = error term (cost shock, model specification error and/or firm optimization error).

Some of the elements in the above specification are readily observed, such as emissions rates and carbon prices. We construct the inframarginal quantity variable taking into account all offers made by a firm, including both supply and demand units. Furthermore, given that we have fine level data on hourly demand and supply functions, we can construct the ex-post residual demands faced by each firm in each hour, which we use to compute the slope. Finally, given that we have reliable marginal costs estimates, we use these in the regression as a control. However, to the extent that other costs might not be accurately reflected into this variable, we also introduce unit fixed effects.²⁵

The parameters to be estimated are $\Theta = \{\alpha, \beta, \gamma\}$. Testing that the market price fully reflects the opportunity costs of using permits involves testing $\gamma_i = 1$, which is the focus of our results discussion.

Results Table 4.1 presents the structural estimates of opportunity costs. The structural estimations are performed at the firm level. We present six different specifications for each firm, all

²⁴As shown in de Frutos and Fabra (2012), this condition need not hold for those firms not setting the price, or for those units that face a zero probability of being marginal.

²⁵Results are also robust to allowing the marginal cost coefficient to be unit-specific.

Table 4.1: Test based on structural equations

$$b_{ijth} = \alpha_j + \beta c_{jt} + \gamma_i e_j \tau_t + \left| \frac{\partial \widehat{D}_{ijth}^R}{\partial p_{th}} \right|^{-1} Q_{ijth} + \epsilon_{ijth}$$

	All	Firm 1	Firm 2	Firm 3	Firm 4
(1) No FE	1.059 (0.065)	1.034 (0.065)	1.063 (0.051)	1.237 (0.055)	1.099 (0.077)
(2) Unit FE	1.000 (0.023)	0.961 (0.025)	0.874 (0.040)	1.078 (0.034)	1.044 (0.083)
(3) Unit FE + season	0.981 (0.019)	0.949 (0.026)	0.855 (0.034)	1.033 (0.021)	1.023 (0.077)
(4) Spec.3 + RD excluded	0.963 (0.031)	0.948 (0.023)	1.022 (0.033)	0.991 (0.053)	0.830 (0.094)
(5) Spec.4 + Markup (IV)	0.966 (0.042)	0.967 (0.041)	1.029 (0.037)	0.732 (0.074)	0.871 (0.092)
Obs.	16,190	5,244	3,211	5,689	2,046

Notes: Sample from January 2004 to June 2007, includes all thermal units in the Spanish electricity market. Standard errors clustered at the unit level.

of which include marginal cost estimates as controls, as well as unit, weekday, month and year fixed effects. Given the potential endogeneity of the markup component $\left| \frac{\partial \widehat{D}_{ijth}^R}{\partial p_{th}} \right|^{-1} Q_{ijth}$,²⁶ it is instrumented for most specifications. Given that the markup depends on market demand, we use traditional demand-side shifters. Instruments include weather data (temperature, wind speed, humidity), economic activity data, and renewable production, all of which are exogenous to firms' choices. The first four specifications differ on whether we introduce unit fixed effects or on whether we instrument prices. The fifth specification controls for the likely effects of Royal Decree (RD), while the last specification excludes those dates when the RD was in place.

The estimated opportunity cost parameters from the above specifications are close to one for firm 1, which is the largest firm in the market. This also true for firm 2, the second largest firm, when we remove the effect of RD. It has been documented that firm 2 followed an anomalous bidding behavior under RD 3/2006,²⁷ thus suggesting that the estimates might be biased in the other specifications. The parameter estimated for the two other firms is also close to one for most specifications, but it varies more across specifications. One possible explanation for this result is that small firms do not behave as closely to optimal bidding as bigger players, as shown in [Hortaçsu and Puller \(2008\)](#). Another possible explanation is that these firms have a smaller portfolio of

²⁶Note that the markup depends on equilibrium prices and it is therefore endogenous. One way to see why it can be endogenous is to consider variation within generator. Everything else equal, the markup will tend to be smaller when a generator has a particularly low cost draw, as it comes earlier in the merit order and thus, the inframarginal quantity is smaller.

²⁷The Spanish Regulatory Authority, CNE, published a report in July 2006 describing this anomalous behavior.

generators with less variation in marginal costs and emissions rates, making the identification more sensitive to the controls and the included sample.

Finally, Table A.1 in the appendix presents alternative specifications to the ones presented in this section. In particular, it uses an expanded data set in which observations “close to being marginal” are also used, which depends on the bandwidth parameter. One can see that the results are similar, overall providing evidence consistent with full internalization.

This test has relied on an explicit model of strategic behavior in this market, at the expense of putting some structure on the behavioral assumptions regarding equilibrium strategies. Our next test is less demanding in terms of the underlying strategic assumptions.

4.2 Test based on participation decisions

To assess the response of generators to carbon costs, we model the choice of a production unit deciding whether to produce or not on a given day, as in Reguant and Ellerman (2008). Given that generating units produce on those days in which their overall costs of turning on are below the market price, the decision to produce or not on a given day is a function of the expected average price that the unit is going to get for that day, as well as the costs that the unit incurs in producing, including the opportunity costs of using emission permits. A dynamic continuation value might also affect that decision. Furthermore, if the unit is owned by a large firm, its decision might also depend on the effect that turning on or off a given unit has on market prices, and thus on the revenues accrued through the firm’s remaining units.

The decision can be represented in a reduced-form fashion with the following inequality:

$$on_{jt} = \begin{cases} 1 & \text{if } p_t \geq c_{jt} + e_j\tau_t + u_{jt}; \\ 0 & \text{otherwise,} \end{cases} \quad (4.2)$$

where

$$\begin{aligned} p_t &= \text{daily electricity price,} \\ c_{jt} &= \text{marginal cost of a given unit,} \\ e_j &= \text{emissions rate of unit } j, \\ \tau_t &= \text{daily cost of the CO}_2 \text{ allowances,} \\ u_{jt} &= \text{other opportunity costs for a given unit.} \end{aligned}$$

The above equation suggests using the following strategy to identify whether firms are internalizing emissions costs or not:

$$on_{jt} = \alpha_j + \beta_1 p_{jt} + \beta_2 c_{jt} + \gamma e_j \tau_t + X_{jt} \beta_3 + \omega_t \delta + \epsilon_{jt}, \quad (4.3)$$

where, on top of the variables defined above, we have introduced unit fixed-effects α_j , a vector of time fixed-effects ω_t (day of the week, month and year), and a vector of other variables affecting opportunity cost of units X_{it} , such as the status of unit (on/off) and inframarginal output.

In the above framework, a test for cost internalization becomes a test of $\beta_1 = -\gamma$, i.e. we

test whether changes in expected prices have the same effect, but with opposite sign, as changes in emission costs. The rationale is that these two changes have the same impact on the unit’s expected profits, and hence should have a quantitatively similar effect on the unit participation decisions. This approach has the advantage of allowing for a normalization of coefficients that does not rely on cost data.

Alternatively, one could compare the coefficient on the marginal cost and the coefficient on the carbon cost to test whether changes in these two components affect the participation decision equally. However, this test might be biased to the extent that, unlike prices or emissions costs, the marginal cost variable is not directly observable and might thus suffer from a measurement error. We have therefore decided to use marginal cost estimates as a control rather than part of the test itself.

It is also important to control for other elements that affect the opportunity cost of a given unit when turning on/off. One of the controls that is particularly relevant is whether the unit was on or not the previous day, as this affects the startup costs of the unit, and these can be large. Similarly, it is important to control for the continuation value of starting up, given that the startup decision commonly involves more than one day. The day of the week dummies and month dummies also capture differences in the continuation value, which depends on weekly and seasonal fluctuations.

Given that this is a market in which there is potential for exercise of market power, we also control for variables that are known to affect bidders’ incentives to withhold capacity. For instance, the greater the firm’s inframarginal production, the greater the impact of the unit’s participation decision on the firm’s profits through its effect on prices. Accordingly, in some specifications we control for the inframarginal quantity of the firm owning the unit, as in [Wolfram \(1998\)](#).

In our last specification, we remove the dates for which the Royal Decree 3/2006 applied, as described in section 3.2, as this might have affected firms’ strategic decisions, potentially biasing the results.

Results Table 4.2 presents the reduced-form test of cost internalization based on units’ participation decisions. The table reports the coefficients on price and emissions costs under different specifications. The dependent variable is whether a unit is on or off at a given day, which is regressed on the average market price, the unit emissions cost and a rich set of controls. Price is instrumented for most specifications with demand shifters, using the same instrumental variables as the ones described in section 4.1. The value of the ratio $-\gamma/\beta_1$ is also included in the table with an F-test of the equality $\beta_1 = -\gamma$, which is the proposed internalization test.

The time controls included in the regressions are aimed at capturing the opportunity cost of the units not included in the basic specification. In particular, the costs for a thermal plant when deciding to run or not for a given day depend crucially on whether the unit is already turned on, which becomes a state variable at the decision stage ([Reguant, 2011](#)). For this reason, we also run the regressions when the plants are turned off at the beginning of the day.²⁸ The advantage of

²⁸[Fowle \(2010\)](#) uses a similar approach in the context of the NO_x Budget Program.

Table 4.2: Test based on operational patterns

$$on_{jt} = \alpha_j + \beta_1 p_{jt} + \beta_2 c_{jt} + \gamma e_j \tau_t + X_{jt} \beta_3 + \omega_t \delta + \epsilon_{jt},$$

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$p_t [\beta_1]$	8.766 (0.607)	10.697 (0.937)	5.673 (0.917)	5.668 (0.916)	6.032 (0.938)	5.818 (0.927)	7.198 (1.126)
$e_i \tau_t [\gamma]$	-6.799 (1.652)	-8.423 (1.546)	-6.016 (1.105)	-5.932 (1.112)	-5.302 (1.928)	-5.674 (1.831)	-5.625 (2.845)
γ/β_1	0.776	0.787	1.060	1.047	0.879	0.975	0.782
F-test ($\gamma=\beta_1$)	0.193	0.137	0.717	0.780	0.728	0.942	0.619
Obs.	85,163	85,163	38,473	38,473	38,473	38,473	23,181
Mg. cost control	Y	Y	Y	Y	Y	Y	Y
Price IV	N	Y	Y	Y	Y	Y	Y
Only OFF	N	N	Y	Y	Y	Y	Y
Infra. Quantity	N	N	N	Y	Y	Y	Y
YearXMonth FE	N	N	N	N	Y	Y	Y
Weekd.XUnit FE	N	N	N	N	N	Y	Y
RD Excluded	N	N	N	N	N	N	Y

Notes: Sample from January 2004 to June 2007, includes all thermal units in the Spanish electricity market. All regressions include unit, weekday, month, year and Royal Decree fixed effects. Standard errors clustered at the unit level. For easier comparison, prices and emissions costs are normalized in $\text{€}10^{-3}$.

including only units that are turned off is that the estimated fixed effects and the day of the week controls are conditional on the unit not being operative. Therefore, the controls will capture, at least in part, the presence of startup costs.²⁹

The results in Table 4.2 are consistent with the emissions price reflecting the opportunity cost of the permits. In particular, $-\gamma/\beta_1$ is close to 100% in the more complete specifications, and it is in any case above 75% in all of them. In the specifications in which we control for the status of the unit, the estimated ratios are very close to 100%. The estimated ratios are stable across these different specifications, supporting the robustness of the hypothesis that firms fully internalize the costs of emissions.

We include in the appendix additional specifications and results. Table A.2 presents several robustness checks to the main specifications. It presents a set of regressions in which we use the unit-specific quantity weighted market price, instead of the average price; a set of regressions in which only the units that are on are used; and a set of regressions in which the coefficients on input and the inframarginal quantity are allowed to be different by type of fuel and firm, respectively. The point estimates are all within 0.78 and 1.06, and we cannot reject full internalization. The

²⁹The estimated time effects go in the expected direction. For example, the day of the week has a declining value as the week progresses, which is consistent with the continuation value of starting up being lower in the middle of the week or during the weekend.

most flexible specification has a coefficient of 0.975. Table A.3 presents estimates of the ratios when the regressions are performed separately for each of the four main firms. We find that the ratio is close to one for most firms, except for firm 3, which, in line with the structural results, appear to be more sensitive to the specification used.

In sum, the evidence reported in this section is consistent with the hypothesis that firms perceived the CO₂ price as the relevant opportunity cost of generating emissions.

5 Evidence on Pass-through

In this section, we discuss the empirical strategy and results regarding the estimation of the pass-through in this market that arises due to carbon emissions prices. One important clarification is that the quantification is focused on isolating the partial effect of carbon prices on electricity prices, holding the rest of input costs fixed. The measured pass-through does not account for general equilibrium changes that could have been induced by the policy. Most importantly, the computed pass-through will not include the potential effect of an EU-wide cap-and-trade market on the relative prices of coal and gas. The pass-through rate that we measure does not include any effects of the EU-ETS on investments either. In summary, our pass-through estimate has to be interpreted as a short-run partial-equilibrium measure.

When measuring the pass-through, we differentiate two different measures: the price pass-through rate and the cost pass-through rate. The *price pass-through* measures the effect of a one euro increase in the price of CO₂ on the electricity price. The *cost pass-through* takes into account that the marginal cost shock faced by the firms depends on which technologies are setting the price. It measures the effect on electricity prices of a one euro increase in the marginal cost of the technology setting the price.

These two measures are tightly related to each other, but they emphasize two different aspects that are crucial when considering the impacts of cap-and-trade. The price pass-through emphasizes the market impacts of the policy, as it is a measure of electricity prices increases due to the introduction of pollution costs. It ultimately measures the impacts faced by final consumers and industrial manufacturers, and is thus very policy-relevant. The cost pass-through emphasizes more directly the role of demand and supply in the market. With inelastic demand, homogeneous producers and competitive behavior, models predict that the cost pass-through should be equal to one. Deviations from such prediction can be used to identify the market structure in this industry.

Section 5.1 performs a structural computation of the marginal pass-through rates using auction-level data. These simulated pass-through rates need to be interpreted as the pass-through rates that we would expect in this market given the cost heterogeneity present in the market and the market structure. Section 5.2 presents a reduced-form quantification of the pass-through based on observed equilibrium prices and quantities and therefore does not rely heavily on the bidding data.

5.1 Quantification based on simulated price responses

Given the previous evidence, we assume that the firms perceived the market price as the opportunity cost of emissions. Under this assumption, as presented in section 4.1, the equilibrium bidding equations at the wholesale electricity auction are given by,

$$b_{ijth} = \alpha_j + \beta c_{jt} + e_j \tau_t + \left| \frac{\partial \widehat{D}_{ith}^R}{\partial p_{ith}} \right|^{-1} (1 - \theta_i) Q_{ith} + \epsilon_{ijth}. \quad (5.1)$$

We use these optimal bidding equations to simulate the marginal bidding response of firms to changes in CO₂ prices. We compute changes in optimal bids given small changes in the emissions cost, so that we can safely take participation decisions as given.³⁰ In particular, we compute the counterfactual in which the cost of emissions increases by one euro, i.e. $\tau' = \tau + 1$. We then compute implied pass-through rates.³¹

As shown in equation (5.1), an increase in carbon prices can affect optimal bids in two ways. First, it affects marginal costs directly, through the component $e_j \tau_t$. Second, if firms are strategic, it can affect the markup component by changing the shape of the residual demand as well as the firm's net inframarginal production.

The cost shock might also affect bidding by units that do not necessarily face a cost shock, particularly hydro units. In order to account for the opportunity cost of hydro bids, we assume that they would modify them in the same manner as their neighboring bids, so that their relative strategic position in the supply curve would not change. Even though this is a limitation, this is a rough way to capture the change in hydro bids.³²

Table 5.1 represents a matrix of the simulated prices that we compute. In order to separate demand and supply channels that affect the pass-through, we first compute a counterfactual in which we hold demand fixed and we change bids in a competitive fashion.³³ In these simulations, the only change is an increase in bids corresponding to a one euro increase in the permits costs, i.e. bids go up by e_j . In this setting, the cost pass-through should be equal to one, except for cases in which there is substitution across cleaner technologies at the margin, in which case the pass-through could be above or below one. Second, we allow demand response, based on the observed demand curve in the market.³⁴

The third and fourth counterfactuals that we compute are analogous to the first two, but they

³⁰Characterizing the optimal startup decision is beyond the scope of this paper. See Reguant (2011) for a computation of optimal strategies in the presence of fixed costs. Given that we are evaluating changes in bids for marginal increases in emissions costs, participation decisions are likely to have a minor effect in the results.

³¹In order to compute optimal prices, we need to modify not only bids that are ex-post marginal, but bids that are close to being marginal. Our implicit assumption is that bids close to the observed market price have a positive probability to set the price and therefore reflect the marginal incentives faced by the firm.

³²Modeling the dynamic decision of hydro is beyond the scope of this paper. An alternative simple shortcut would have been to fix the amount of water used in a given month, and re-arrange as a function of marginal prices, as in (Borenstein et al., 2002). We plan to consider this extension in future versions of the paper.

³³It is important that the counterfactuals is about *changes* in bids. The baseline bid levels do not necessarily represent competitive bids, as discussed below.

³⁴Note that this demand curve will tend to be more inelastic than long-run electricity demand, so the estimate provides an upper bound on pass-through once demand response is accounted for.

Table 5.1: Simulated Bids and Pass-through Counterfactuals

Inelastic Demand Only MC Change	Demand Response Only MC Change
Inelastic Demand MC + Markup Change	Demand Response MC + Markup Change

allow the markup component to endogeneously change with the cost shocks. The markup can change for two reasons: the inframarginal quantity might change if there are endogenous changes of merit order within the firm, and the slope of the residual demand might change as a result of other firms changing their bids.

Ideally, one would like to compute the overall equilibrium given the new prices. Given that we compute perturbations around the equilibrium price, we follow the approach of looking only at best response deviations and examine whether the markup impacts are substantive. We then update prices for all firms with the new markups and examine the impact on price. Unfortunately, such counterfactual cannot be computed in one step. With this approach, we intend to capture, to first order, some of the changes in markups in this market.

Results First, we present results in which we hold demand fixed and we only adjust firm bids through an increase in marginal costs. We present these counterfactuals first as they are very useful to provide an intuition behind the pass-through distribution that we observe in the data. Without cost heterogeneity and inelastic demand, the cost pass-through should be exactly equal to one in this setting. Therefore, any deviations from pass-through rates that are different than one comes through the heterogeneity of marginal costs in the underlying supply curve.

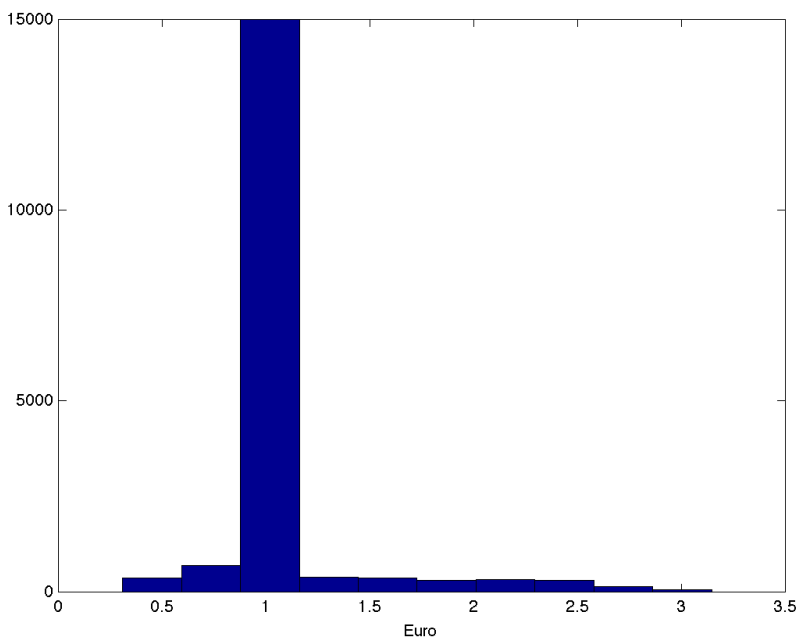
Figure 5.1 shows the distribution of the *cost pass-through* rates, i.e. taking into account the emissions rate of the marginal unit. Even though it is centered around 1, we see some departures when there is substitution away from one technology to another. Note that if the marginal technology switches from coal to gas, this results in a cost pass-through below 1, whereas the opposite is true if the marginal technology switches from gas to coal.

Given relative prices for coal and gas during the sample period and the limited extent of substitution between coal and gas unless CO₂ prices are high enough, there remains the question of whether the observed cost pass-through presents heterogeneity that is consistent with the exercise of market power. In particular, if there are big firms that have a particular generation mix (coal and gas), and fringe players that only have gas, one could expect to see more substitution than in a competitive setting.³⁵

To explore this claim, we perform the same pass-through rate calculation as above, i.e. with inelastic demand and increase in bids proportional to the emissions rate of each plant. However,

³⁵The potential for substantial production inefficiency in the particular case of the Spanish electricity market has been pointed out in (Kühn and Machado, 2004).

Figure 5.1: Distribution of pass-through rates with inelastic demand and marginal cost bidding changes



The histogram represents the effect of a one euro increase in the marginal costs of the marginal technology on the electricity price. The sample is restricted to hours in which the marginal unit has a positive emission rate.

Table 5.2: Pass-through (PT) Results

	Price Pass-through		Cost pass-through	
	Inelastic	Elastic	Inelastic	Elastic
Competitive	0.700 (0.277) [0.377, 0.939]	0.599 (0.333) [0.371, 0.833]	1.032 (0.184) [1.000, 1.000]	0.911 (0.381) [0.998, 1.000]
Only MC Change	0.696 (0.275) [0.372, 0.939]	0.505 (0.382) [0.359, 0.836]	1.061 (0.265) [1.000, 1.000]	0.789 (0.531) [0.695, 1.000]
MC + Markup Change	0.695 (0.486) [0.245, 0.837]	0.470 (0.562) [0.371, 0.956]	1.084 (0.790) [0.377, 1.000]	0.753 (0.928) [0.961, 1.114]

Notes: Sample from January 2005 to March 2006. Period with Royal-Decree 3/2006 is excluded. Standard deviation of passthrough distribution in parenthesis. Interquantile range in brackets. Competitive counterfactual replaces original marginal bids of thermal plants with engineering cost estimates.

we take engineering costs as the baseline price bid level, instead of observed bids. We find that, using engineering estimates for marginal cost prices, departures in cost pass-through rates due to merit order switching occur in 11.03% of the hours of the sample.³⁶ On the contrary, merit order switches occur 16.91% of the hours using observed bids.³⁷ These results suggest that part of the observed merit order switching in the cost pass-through rate is due to different strategic market positions across sellers.

Finally, we perform the counterfactuals allowing for both markup changes and demand response as implied by the wholesale demand curves. Table 5.2 presents average pass-through rates for all the cases considered. Discussion TBA.

5.2 Quantification based on observed price responses

A more conventional approach to estimating pass-through rates is to regress the wholesale electricity price on allowance prices. Given that there is substantial variation in CO₂ prices, one can identify the *price pass-through* from observed electricity price responses, and not from the structural bidding equations.

The baseline regression to identify the degree of price pass-through is:

$$p_{th} = \rho\tau_t + X_{th}\beta_0 + Z_{th}^S\beta_1 + Z_{th}^D\beta_2 + \omega_{th}\delta + \epsilon_{th}, \quad (5.2)$$

where

- p_{th} = hourly electricity price,
- τ_t = daily cost of the CO₂ allowances,
- X_{th} = common controls,
- Z_{th}^S = supply-side exogenous shifters and controls,
- Z_{th}^D = demand-side exogenous shifters and controls,
- ω_{th} = time fixed-effects (hour, day of week, month and year).

where ρ is our parameter of interest as it identifies the equilibrium price pass-through. Strategies to recover the marginal cost pass-through are discussed below.

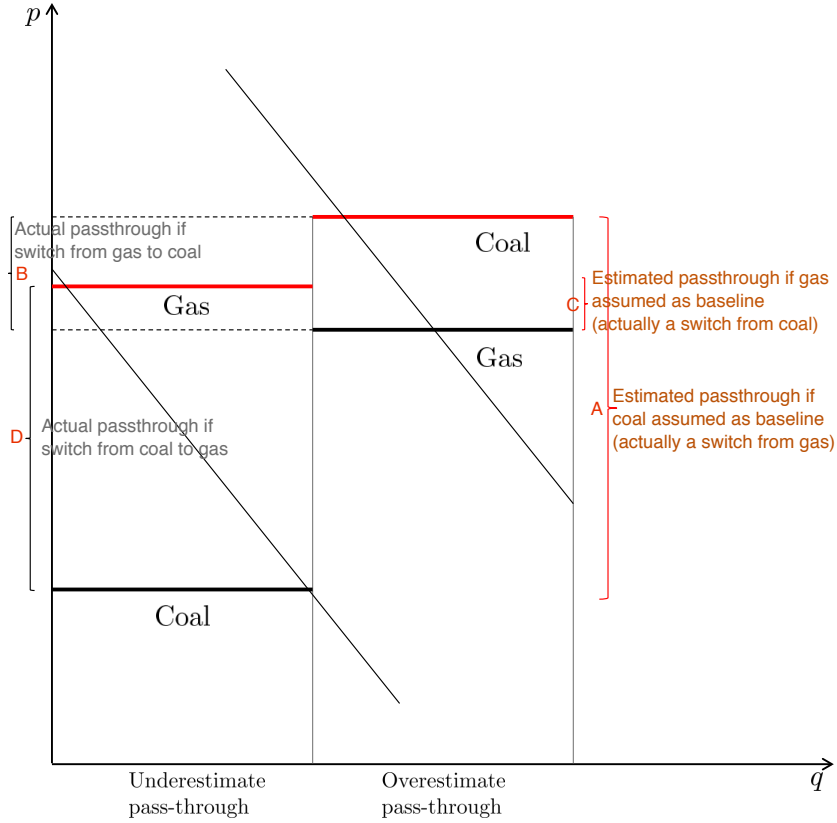
The specification includes year and month, day of the week and hour fixed effects to control for potential trends and seasonality within the year. We also allow for the hourly and day of the week fixed effects to be different for every month. As common controls, we include European fuel prices of coal, gas and oil, as well as their quadratic terms and quadratic terms of their differences. On the demand side, we include weather, economic activity indicators and the other controls used in the cost internalization analysis.³⁸ We allow weather variables to have a different effect on price

³⁶We define departures from unitary pass-through if the pass-through is not between 99.9%-100.1% to avoid counting small fluctuations in the pass-through. Other definitions are also consistent with these differences, although the percents are larger across the board as the definition gets narrower.

³⁷If we exclude night hours, in which some power plants might have different incentives to stay online over night, we still find a difference between competitive and strategic counterfactuals in the amount of switching (6.00% vs 9.43%, respectively).

³⁸Economic activity indicators include a production index provided by the Spanish government and quarterly

Figure 5.2: Estimating cost pass-through with heterogeneous cost shocks



depending on the month (for example, it is very different a warm day in the winter, which will tend to reduce electricity consumption, than a warm day in the summer). On the supply side, we also include controls for renewable capacity and output.

Similar to the internalization rate regressions, the main identifying assumption behind the pass-through estimate is that, once we control for all relevant factors that might be correlated with the electricity market, the remaining variation of the CO_2 price can be considered exogenous. Note that the assumption in this context is stronger than before, as the equilibrium pass-through equation is a function of both demand and supply factors. One would expect many variables affecting demand to be correlated with the prices of CO_2 (e.g. growth rates, exchange rates, etc.), and therefore we need to be very exhaustive when controlling for all relevant factors.

Identifying the *cost pass-through* is more challenging in this context, as one needs to control for the emissions rate of the unit that would have set the price in the absence of the cost shock, which is not observed. Using the actual emissions rate of the unit that is at the margin could provide a biased estimate of the cost pass-through, as the effective cost shock at the margin is endogenous. A regression without accounting for this endogeneity can generate biased estimates in the presence of merit order switching, as exemplified in figure 5.2. The red lines represent the

growth rates in Spain.

Table 5.3: Reduced-form price pass-through measures

$$p_t = \rho EUA_t + X_t\beta_0 + Z_t^S\beta_1 + Z_t^D\beta_2 + \omega_t + \epsilon_t,$$

	(1)	(2)	(3)	(4)	(5)
$EUA_t(\rho)$	1.172 (0.009)	1.145 (0.030)	0.921 (0.081)	0.593 (0.053)	0.440 (0.086)
Obs.	30,648	30,648	18,960	30,648	18,960
Basic controls	N	Y	Y	Y	Y
RD Excluded	N	N	Y	N	Y
Month-year FE	N	N	N	Y	Y

Notes: Sample from January 2004 to June 2007, includes all thermal units in the Spanish electricity market. Robust standard errors.

observed prices, whereas the black lines represent the costs of coal and gas absent any CO₂ prices. With CO₂ prices, there is a switch and gas comes first in the merit order. If there is such merit order switching between coal and gas, one will tend to overestimate the pass-through rate when coal is observed at the margin (one would measure A instead of B, A > B) and underestimate the pass-through rate in periods when gas is observed at the margin (one would measure C instead of D, C < D).

In order to address this concern, we use a simulation approach to create a measure of the marginal emissions rate that would have been at the margin if CO₂ prices were zero. We regress the electricity price on the emissions costs instrumenting the measure of emissions costs with the simulated emissions cost if the counterfactual baseline marginal technology were to set the price.

Results Table 5.3 presents estimates of price pass-through rates in this market. The results reveal substantial heterogeneity across specifications. We find that the estimated pass-through rate has a wide range depending on the specifications, ranging from 0.43-1.17.

The raw relationship between electricity prices and carbon prices is 1.17, as shown in specification (1). We get similar results if we include year and month fixed effects, as well as other controls: hour-month fixed effects, daily temperature and wind speed interacted with month of the year to allow for seasonality, wind output, day of the week dummies, holiday index, activity index, Spanish GDP, coal, gas and oil linear and quadratic prices, as well as time trends.³⁹ In specification (3), we restrict the sample to exclude the royal-decree period. The price pass-through is close to 1.

Specifications (1)-(3) might have some omitted variables bias, as it is difficult to fully control for all changes in demand and supply that could be potentially correlated with the evolution of the CO₂ price. To further address this concern, we include month of sample fixed effects. The results change substantially. In specification (4) and (5), we find that the estimated pass-through

³⁹The holiday index and the activity index are measures created by the System Operator to estimate demand conditions in the market based on economic activity and labor patterns.

is between 41-59%, depending on the specification. These more complete specifications seem to line up best with our simulated estimates.

Table 5.4 presents estimates of the cost pass-through rates. In order to estimate the cost pass-through, we separate the sample in two: one sample includes those hours in which coal technology would have been at the margin, and the other sample includes those hours in which CCGT would have been at the margin. We instrument the actual emissions cost at the margin with the emissions costs of the technology that would have been at the margin. All specifications include the most complete set of controls used in the price pass-through regressions.⁴⁰

One can see that the pass-through rate estimated with the OLS specification, presented in column (0), appears to be attenuated. Specifications (1)-(2) present the results for both technologies pooled together. We find evidence that the cost pass-through rate is lower when coal is at the margin than when gas is at the margin. The coal pass-through rate is below one, which is consistent with the presence of switching in the merit order from coal to gas induced by the policy. When coal would have been at the margin in the absence of merit order switching, we find a pass-through lower than one. As a robustness check, we allow all the coefficients on the other controls to be different in each subsample, in specification (3)-(6). We find that the results do not change substantially, although the pass-through rate appears to be lower if we exclude the period from the Royal Decree.

The results provide evidence that, given the high degree of internalization in this market, the implied cost pass-through rates were close to one. The evidence is also in line with merit order switching from dirty to cleaner technologies. Unfortunately, given the number of controls and limited within-month variation in the data, the standard errors are relatively large and we cannot reject that the cost pass-through is equal to one for all technology groups.

Combining the reduced form evidence with the previous structural approach, we find intermediate levels of price pass-through (around 40-60%) and levels of cost pass-through close to one. The simulated results suggest that there is scope for an attenuated cost pass-through, which arises in the presence of substitution from coal to gas and residual demand response. The reduced-form evidence is also consistent with incomplete price pass-through. The cost pass-through rate is also close to one in the regression results, and we also find evidence of heterogeneous rates due to differences in emissions costs.

6 Conclusions

We have presented an empirical assessment of the internalization and pass-through rates due to the introduction of carbon permits in the Spanish electricity market. To quantify both rates, we have analyzed results from both reduced-form and structural models. The analysis has benefited from two important features of the market. First, we have exploited the fact that the evolution of European-wide CO₂ prices can be considered exogenous to the Spanish electricity market. Second,

⁴⁰Similar to the price pass-through regression, results for the cost pass-through rate changes depending on the number of controls included. We include a full battery of additional specifications in table A.4 in the appendix. Similar to the case of the price pass-through, we find the set of month of sample fixed effects to matter the most.

Table 5.4: Reduced-form **cost pass-through** measures

$$p_t = \rho e_{jt} EU A_t + X_t \beta_0 + Z_t^S \beta_1 + Z_t^D \beta_2 + \omega_t + \epsilon_t,$$

			Coal subsample		CCGT subsample		
	(0)	(1)	(2)	(3)	(4)	(5)	(6)
$e_{jt} EU A_t(\rho)$ (Coal)	0.198 (0.047)	0.800 (0.142)	0.625 (0.260)	0.822 (0.104)	0.631 (0.166)		
$e_{jt} EU A_t(\rho)$ (CCGT)	0.382 (0.030)	1.194 (0.106)	1.035 (0.197)			1.088 (0.142)	0.886 (0.273)
Obs.	25,398	25,398	14,765	13,076	8,722	12,322	6,043
Instruments	N	Y	Y	Y	Y	Y	
RD Excluded	N	Y	N	Y	N	Y	
Month-year FE	Y	Y	Y	Y	Y	Y	

Notes: Sample from January 2004 to June 2007, includes all thermal units in the Spanish electricity market. Robust standard errors. Carbon costs of marginal unit instrumented with average emissions costs if the sampled technology where to set the price in counterfactual without no carbon prices.

the richness of the micro-level data has allowed us to perform structural estimations without imposing strong assumptions on the shape of the demand and supply functions, nor on the way firms behave in electricity markets.

The empirical results support the hypothesis that firms internalize the full cost of emissions in this market, specially the bigger firms. Also, this generally translates into cost pass-through rates close to one. In spite of cost pass-through being close to one, we find evidence of substitution from dirtier (coal) to cleaner (gas) plants. The implied effects on price are less than one, given the heterogeneity in emissions costs across technologies, being on average around 45-60%.

References

- Bahringer, C. and Lange, A. (2012). *The EU Emissions Trading System*. Elsevier.
- Besanko, D., Dranove, D., and Shanley, M. (2001). Exploiting a Cost Advantage and Coping with a Cost Disadvantage. *Management Science*, 47(2):221–137.
- Besanko, D., Dubé, J.-P., and Gupta, S. (2005). Own-Brand and Cross-Brand Retail Pass-Through. *Marketing Science*, 24(1):123–137.
- Bonnet, C., Dubois, P., and Villas Boas, S. B. (2012). Empirical evidence on the role of non linear wholesale pricing and vertical restraints on cost pass-through. *Review of Economics and Statistics*.

- Borenstein, S., Bushnell, J., and Wolak, F. (2002). Measuring Market Inefficiencies in California's Restructured Wholesale Electricity Market. *American Economic Review*, 92(5):1376–1405.
- Bushnell, J., Chong, H., and Mansur, E. (2009). Profiting from Regulation: An Event Study of the European Carbon Market. Working Paper 15572, National Bureau of Economic Research.
- Bushnell, J., Chong, H., and Mansur, E. (2011). Profiting from regulation: Evidence from the european carbon market.
- de Frutos, M. A. and Fabra, N. (2012). How to allocate forward contracts: the case of electricity markets. *European Economic Review*, 56(3):451–469.
- Ellerman, A. D., Buchner, B. K., and Carraro, C. (2007). *Allocation in the European Emissions Trading Scheme*. Cambridge University Press.
- Ellerman, A. D., Convery, F. J., and de Perthuis, C. (2010). *Pricing Carbon: The European Union Emissions Trading Scheme*. Cambridge University Press.
- Fabra, N. and Toro, J. (2005). Price wars and collusion in the spanish electricity market. *International Journal of Industrial Organisation*, 23(3-4):155–181.
- Fowle, M. (2010). Allocating Emissions Permits in Cap-and-Trade Programs: Theory and Evidence. Technical report, University of California, Berkeley.
- Goeree, J. K., Holt, C. A., Palmer, K., Shobe, W., and Burtraw, D. (2010). An Experimental Study of Auctions versus Grandfathering to Assign Pollution Permits. *Journal of the European Economic Association*, 8(2-3):514–525.
- Goldberg, P. K. and Hellerstein, R. (2008). A Structural Approach to Explaining Incomplete Exchange-Rate Pass-Through and Pricing-to-Market. *American Economic Review*, 98(2):423–29.
- Green, R. and Newbery, D. (1992). Competition in the british electricity spot market. *Journal of Political Economy*, 100(5):929–53.
- Hortaçsu, A. and Puller, S. L. (2008). Understanding Strategic Bidding in Multi-unit Auctions: A Case Study of the Texas Electricity Spot Market. *RAND Journal of Economics*, 39(1):86–114.
- Kolstad, J. and Wolak, F. (2008). Using Environmental Emissions Permit Prices to Raise Electricity Prices: Evidence from the California Electricity Market.
- Kühn, K.-U. and Machado, M. (2004). Bilateral Market Power And Vertical Integration In The Spanish Electricity Spot Market. Working Paper 2004-0414, CEMFI.
- Marion, J. and Muehlegger, E. (2011). Fuel Tax Incidence and Supply Conditions. Working Paper 16863, National Bureau of Economic Research.

- McGuinness, M. and Ellerman, A. D. (2008). CO₂ Abatement in the UK Power Sector: Evidence from the EU ETS Trial Period. Working paper, Massachusetts Institute of Technology, Center for Energy and Environmental Policy Research.
- Parsons, J. E., Ellerman, A. D., and Feilhauer, S. (2009). Designing a US Market for CO₂. Working papers, Massachusetts Institute of Technology, Center for Energy and Environmental Policy Research.
- Reguant, M. (2011). The Welfare Effects of Complementary Bidding Mechanisms. Massachusetts Institute of Technology.
- Reguant, M. and Ellerman, A. D. (2008). Grandfathering and the endowment effect - an assessment in the context of the spanish national allocation plan.
- Sijm, J., Neuhoff, K., and Chen, Y. (2006). CO₂ Cost Pass-Through and Windfall Profits in the Power Sector. Technical report.
- von der Fehr, N. H. and Harbord, D. (1993). Spot market competition in the uk electricity industry. *Economic Journal*, 103:531–546.
- Weyl, E. G. and Fabinger, M. (2012). A Restatement of the Theory of Monopoly. *SSRN eLibrary*.
- Wolfram, C. (1999). Measuring duopoly power in the british electricity spot market. *American Economic Review*, 89(4):805–826.
- Wolfram, C. D. (1998). Strategic Bidding in a Multiunit Auction: An Empirical Analysis of Bids to Supply Electricity in England and Wales. *The RAND Journal of Economics*, 29(4):703–725.
- Wrake, M., Myers, E., Burtraw, D., Mandell, S., and Holt, C. (2010). Opportunity Cost for Free Allocations of Emissions Permits: An Experimental Analysis. *Environmental & Resource Economics*, 46(3):331–336.
- Zachmann, G. and Hirschhausen, C. (2008). First Evidence on Asymmetric Cost Pass-through. Working papers, Massachusetts Institute of Technology, Center for Energy and Environmental Policy Research.

A Additional Figure and Tables

Table A.1: Test based on structural equations - Bandwidth sensitivity

$$b_{ijth} = \alpha_j + \beta c_{jt} + \gamma_i e_j \tau_t + \left| \frac{\partial \widehat{D}_{ijth}^R}{\partial p_{th}} \right|^{-1} Q_{ijth} + \epsilon_{ijth}$$

	Firm 1	Firm 2	Firm 3	Firm 4
<i>bw</i> = 1 Euro	0.981 (0.022)	0.966 (0.029)	0.989 (0.027)	0.805 (0.064)
Obs.	475,318	508,233	579,641	227,623
<i>bw</i> = 2 Euro	0.976 (0.020)	0.959 (0.026)	0.995 (0.028)	0.783 (0.062)
Obs.	714,699	692,069	687,914	255,182
<i>bw</i> = 3 Euro	0.982 (0.017)	0.957 (0.026)	1.002 (0.030)	0.755 (0.061)
Obs.	752,763	729,210	705,462	260,284
<i>bw</i> = 4 Euro	0.988 (0.016)	0.955 (0.026)	1.005 (0.032)	0.727 (0.060)
Obs.	752,783	729,836	705,694	260,364
<i>bw</i> = 5 Euro	0.992 (0.016)	0.952 (0.026)	1.003 (0.033)	0.701 (0.061)
Obs.	752,783	729,836	705,694	260,364

Notes: Sample from January 2004 to June 2007, includes all thermal units in the Spanish electricity market. It uses specification 4 in table 4.2.

Table A.2: Test based on operational patterns, additional specifications

$$on_{jt} = \alpha_j + \beta_1 p_{jt} + \beta_2 c_{jt} + \gamma e_j \tau_t + X_{jt} \beta_3 + \omega_t \delta + \epsilon_{jt},$$

	Weighted Price		Only On		Flexible coeff.	
$p_t [\beta_1]$	5.116 (0.859)	5.316 (0.847)	4.842 (0.610)	4.662 (0.575)	4.536 (0.544)	5.562 (0.836)
$e_i \tau_t [\gamma]$	-5.750 (1.141)	-6.143 (1.158)	-3.940 (0.745)	-3.927 (0.772)	-3.947 (0.808)	-5.911 (1.188)
γ/β_1	0.776	0.787	1.060	1.047	0.879	0.975
F-test	0.193	0.137	0.717	0.780	0.728	0.942
Obs.	38,473	38,473	46,690	46,690	46,690	38,473
Only OFF	Y	Y	N	N	Y	Y
Only ON	N	N	Y	Y	N	N
Mg. cost control	N	Y	N	Y	Y	Y
UnitXMg. cost control	N	Y	N	Y	Y	Y
FirmXInfrac control	N	N	N	N	Y	Y
Firm*net supply	N	N	N	N	N	Y

Notes: Sample from January 2004 to June 2007, includes all thermal units in the Spanish electricity market. All regressions include unit, weekday, month, year and Royal Decree fixed effects. Standard errors clustered at the unit level. Prices and emissions costs are normalized in $\text{€}10^{-3}$.

Table A.3: Test based on operational patterns, additional specifications

$$on_{jt} = \alpha_j + \beta_1 p_{jt} + \beta_2 c_{jt} + \gamma e_j \tau_t + X_{jt} \beta_3 + \omega_t \delta + \epsilon_{jt},$$

	Firm 1	Firm 2	Firm 3	Firm 4
$p_t [\beta_1]$	11.630 (2.421)	4.257 (1.372)	5.012 (2.004)	6.489 (1.794)
$e_i \tau_t [\gamma]$	-10.818 (2.518)	-4.779 (1.595)	-7.909 (2.055)	-6.665 (1.059)
γ/β_1	0.930	1.123	1.578	1.027
F-test	0.740	0.708	0.038	0.894
Obs.	8,422	12,016	7,440	1,760

Notes: Sample from January 2004 to June 2007, includes all thermal units in the Spanish electricity market. All regressions include unit, weekday, month, year and Royal Decree fixed effects. Standard errors clustered at the unit level. Prices and emissions costs are normalized in $\text{€}10^{-3}$.

Table A.4: Reduced-form **cost pass-through** measures

$$p_t = \rho e_{jt} EU A_t + X_t \beta_0 + Z_t^S \beta_1 + Z_t^D \beta_2 + \omega_t + \epsilon_t,$$

	(1)	(2)	(3)	(4)	(5)
$e_{jt} EU A_t(\rho)$ (Coal)	1.348 (0.090)	0.657 (0.150)	0.862 (0.140)	0.830 (0.142)	0.800 (0.142)
$e_{jt} EU A_t(\rho)$ (CCGT)	2.012 (0.063)	1.008 (0.112)	1.280 (0.104)	1.230 (0.106)	1.194 (0.106)
Obs.	25,398	25,398	25,398	25,398	25,398
Year-Month FE	N	Y	Y	Y	Y
Month-Hour FE	N	N	Y	Y	Y
MonthXTemp FE	N	N	N	Y	Y
MonthXWind FE	N	N	N	N	Y

Notes: Sample from January 2004 to June 2007, includes all thermal units in the Spanish electricity market. Robust standard errors. Carbon costs of marginal unit instrumented with average emissions costs if the sampled technology where to set the price in counterfactual without no carbon prices.