Pass-Through of Emissions Costs
in Electricity Markets[*]

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Abstract

We quantify the pass-through rate of emissions costs in the Spanish electricity market and explore the channels that generate it (internalization of emissions costs, demand response, market power and heterogeneity of cost shocks). Using rich micro-data, we perform both reduced form and structural estimations without imposing strong assumptions on the shape of demand or supply. We find that 80% of the emissions cost is passed-through to electricity prices. This incomplete pass-through is driven by demand response and market power, and it also reflects the substitution of dirtier technologies by cleaner ones at the margin. Our empirical results also show that firms fully internalized emissions costs.

Keywords: Opportunity costs, pass-through rate, emissions permits, electricity markets.
JEL classification: L13, L94, D44.

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1 Introduction

Cap-and-trade programs constitute a market-based solution to reducing greenhouse gas emissions. The European Emissions Trading System (ETS), currently the largest carbon market in the world, is the European Commission's flagship instrument to fight climate change. 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 and concerns associated with these programs. One of the main benefits of using cap-and-trade for emissions reductions, as opposed to command-and-control methods, is that they allow for an overall reduction in emissions at minimum cost. The fact that all agents face the same price on emissions, i.e., the price of permits in the emissions markets, assures that, absent other distortions, the lowest abatement cost allocation will be achieved.

Cap-and-trade programs have often received major opposition. Among the most contentious elements of cap-and-trade programs is their effect on product market prices and in particular, on rising electricity bills as electricity markets are strongly affected by the emissions regulation.[1] The potential loss of competitiveness, the associated job destruction, and the distributional impacts across industries and regions also rank high in the list of concerns.[2] The extent to which emissions costs can be passed-through to output prices ultimately determines the magnitude of such concerns.

One of the issues that has confounded the debate on the effects of pollution permits on output prices has been the belief that in competitive markets full internalization of permit prices necessarily implies full pass-through.[3] Therefore, evidence on partial pass-through has at times been interpreted as either evidence of firms not fully internalizing the cost of permits or evidence of firms exercising market power, both of which would jeopardize efficiency. Even though this statement is true in some theoretical models, it does not hold as a general statement. Partial pass-through could be explained by either partial cost internalization, market power and demand response, or any combination between them.

In this context, the goal of this paper is twofold: first, to quantify the pass-through rate of emissions costs to electricity prices; and second, to disentangle the determinants of the pass-through rate using micro-level data. In particular, we investigate the response of Spanish electricity firms to the introduction of emissions regulation, taking advantage of the cost shocks induced by changes in emissions permits.

For this purpose, we first quantify the pass-through rate through a reduced-form analysis based on observed equilibrium outcomes. While we follow a standard approach, here we face the challenge of identifying the pass-through rate conditional on the emission rate of the price-setting technology, a measure which is likely to be endogenous. Since the reduced-form estimates are sensitive to the specification considered and do not identify all the channels that explain the pass-through, we also

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[1] Similar concerns have been voiced in the context of the airline industry, as it has recently come into the European Union's emissions trading scheme.

[2] See Martin et al. (2012) for an analysis of the distributional impacts of the EU ETS.

[3] See Ellerman et al. (2010) for a discussion.

rely on a structural approach based on the predictions of the multi-unit auction literature.

Our findings demonstrate that 80% of the increase in emissions costs was passed-through to electricity prices. To understand whether this pass-through is driven by partial cost internalization, we first identify firms' perceived opportunity costs of using permits from the bids they submit into the electricity market. It is well known that, in a frictionless world, the opportunity costs of using permits are given by their market price. However, transaction costs in the emissions markets could reduce the opportunity costs of permits below their market price.[4,5] Different expectations over the permit allocation method could also lead to different estimates: if firms believed that future permit allocations would be based on current emissions, opportunity costs would be below the permit price; in contrast, under grandfathering or auctioning of permits, opportunity costs would be fully captured by permit prices. Last, behavioral biases could stop firms from fully understanding that free permits have an opportunity cost, an issue that is also reminiscent of the concern that auctioning permits will inflate output prices.[6] However, our analysis robustly rejects the hypothesis that partial pass-though could be explained by incomplete internalization of emissions costs.

To understand the role of additional channels such as demand response and market power in explaining partial pass-through, we simulate the response of firms' bidding behavior to marginal increases in the carbon price. We find that demand response has a significant impact in mitigating the pass-through, which is reduced by 20% as compared to the counterfactual with inelastic demand. The analysis also shows substitution from dirtier (coal) to cleaner (gas) technologies, which is more prominent due to the asymmetries in bidding behavior between the large strategic firms and the fringe players.

Studying the pass-through 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 CO_2 contributor in the European Union.[7] Furthermore, the effects of carbon 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 and makes the potential impacts of the policy important.

From an econometric perspective, analyzing the effect of emissions costs in electricity markets has the advantage that European CO_2 prices can be considered exogenous cost shifters to the Spanish electricity companies, as pollution permits are traded across all Member States and across many sectors. Furthermore, there is substantial variation in permit prices during the sample.

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[4]Stavins (1995) argues that transaction costs in emissions markets may be significant, thus reducing trading activity, and increasing abatement costs.

[5]In contrast, financial market imperfections could raise opportunity costs above the permits' market price. Indeed, as argued by a carbon analyst at Deutsche Bank, "The [ETS] was not designed as a scheme to give corporates cheap short-term funding options in the face of a credit crunch meltdown where banks are not lending, but that appears to be what's happening." (The Guardian, 27 January, 2009)

[6]As one energy company official complained: "If emissions allowances are auctioned, that will only lead to 100% of the carbon price being priced into the electricity price, and thus increase it". (Wrake et al. (2010)).

[7]During the first phase of the EU ETS (2005–2007), 60% of total allowances were allocated to the power sector. However, in compliance with the EU's Energy Roadmap 2050, it is expected that the power sector will have to almost fully eliminate its CO_2 emissions by 2050.

Electricity markets are also particularly suited for this analysis. First, there is rich micro-level data, including demand and supply curves, as well as engineered-based cost estimates, that allow us to be flexible in the estimation.[8] And second, the institutions and industrial processes that affect firms' strategic behavior in these markets are well understood,[9] thus allowing to construct a reliable structural framework.

The paper proceeds as follows. After reviewing the related literature, Section 2 describes the context and data of analysis. In Section 3, we introduce a conceptual framework to understand and disentangle the different sources of the pass-through rate. In Section 4, we present reduced-form evidence on the pass-through rate, while in Section 5 we develop a structural model to estimate and decompose the pass-through rate. Section 6 concludes.

Related literature   Other papers have also examined pass-through rates in the context of the EU ETS, though the majority of them rely on a reduced-form analysis only and do not explicitly explore the channels explaining the pass-through rate. For example, Sijm et al. (2006) estimate pass-through rates using equilibrium prices and fuel cost data in the German electricity market.[10] They find pass-through rates that range between 0.60 and 1.17, depending on market conditions. Bushnell et al. (2013) 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.

Our work is also 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.

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

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[8]This 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).

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

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

emissions 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.[11] Bonnet et al. (2013) 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-though rates and their relationship to more-easily-observable industry features remains extremely limited." This work contributes to this line of research.

2 Context and Data

We study the pricing decisions of electricity generators in the Spanish electricity market following the introduction of the European Union's Emissions Trading System (ETS). In this section we briefly describe the context as well as the data that we use for the empirical analysis.

2.1 The European Union Emissions Trading Scheme

The EU ETS is the largest emissions control scheme in the world, affecting almost half of European CO_2 emissions, from approximately 10,000 energy-intensive installations across the EU. It is also the first compulsory international trading system for CO_2 emissions.[12]

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.[13] Each year, companies must surrender enough allowances to cover their emissions, for which they might either use their own allowances or buy them from another firm. Emissions rights can be transacted bilaterally (i.e., company-to-company), brokered (OTC market) or traded in exchanges.[14] Failure to comply implies a €40/ton CO_2 penalty, plus the obligation to purchase the deficit in the market.

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

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[11]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-though rate since electricity is an homogeneous product, and therefore there is a single market price.

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

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

[14]To get some orders of magnitude, in 2005, the market transacted 262 Mt CO_2 (€5.4 billion) through brokers (207 Mt) and exchanges (57 Mt), and a 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%).

Figure 2.1: Evolution of EUA prices during the EU ETS trial period

CO2 Prices
during sample of study
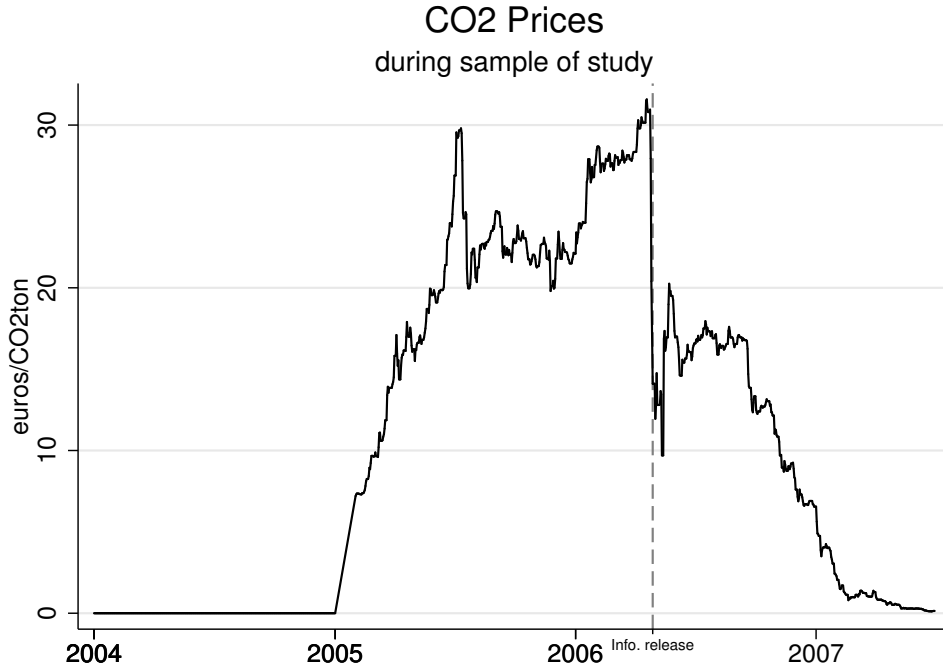
(combustion installations with a rated thermal input exceeding 20MW, mineral oil refineries, coke ovens), production and processing of ferrous metals, the mineral industry (cement clinker, glass and ceramic bricks) and the pulp, paper and board industry. These activities represent around 40% of CO_2 emissions in the European Union, the electricity sector being the largest contributor in the group.[15]

Figure 2.1 shows the evolution of CO_2 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 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 CO_2 prices that will help identify the internalization and pass-through of emissions costs.[16]

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

[16]Bushnell et al. (2013) and Zachmann and Hirschhausen (2008) explicitly exploit this change to analyze the response of firms to changing market conditions.

2.2 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.[17] 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.[18] Participation in these markets is not compulsory, as market participants are 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 electricity. 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 2.1 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 bidding behavior, in some empirical specifications we will remove the dates during which this Royal Decree (RD) was in place.

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

[18]The 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.

Table 2.1: 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.

2.3 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.[19] 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, heat rates, vintage, generating company and geographic location. 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 CO_2 allowance prices (EUA prices), as well as coal, gas, 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).[20] 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

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[19]Data 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.

[20]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). This data are also used in Fabra and Toro (2005).

fuel (as set in international input markets),[21] and the short-run variable cost of operating and maintaining the plant (O&M).

We have also collected annual information on CO_2 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 generators tend to have an emissions rate around 0.35 tons/MWh.

Table 2.2 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 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. Because of their different emissions rates, a high enough price of CO_2 emissions 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. 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.[22]

Table 2.3 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.

3   Conceptual Framework

For the purposes of quantifying and decomposing the pass-through rate of emissions costs, it is useful to first resort to a simplified framework. Consider a simple model in which a firm's costs are

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[21]For 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-Ruhrgas prices. All series are in c€/te. We have downloaded this information from Bloomberg.

[22]The 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 2.2: 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.

Table 2.3: 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.

given by

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

The firm has production costs $C(Q; u)$, where Q is output and is u a cost shock. The firm also produces emissions eQ, where e is the emissions rate per unit of output.[23] The common assumption is that the emissions' permit price, τ, fully reflects the opportunity costs of using permits, so that $\tau e Q$ represents the costs of emissions. However, as already explained, this assumption need not always hold. We thus introduce a parameter, γ, referred to as the "opportunity costs" parameter, which adjusts for the firm's true opportunity costs of using permits: if $\gamma = 1$, opportunity costs are fully captured by the permit price; otherwise, opportunity costs are either below ($\gamma < 1$) or above ($\gamma > 1$) the permit price. The first case could arise in the presence of transaction costs, or under permit allocations based on output updating, while the second case could arise if firms face liquidity constraints that they can relax by selling permits in the emissions market.

Whereas γ is a fundamental parameter of the model, the pass-through rate is an equilibrium outcome. Let $D(p; \epsilon)$ be the demand function, where p is the market price and ϵ is a demand shock; and let $S(p, \tau; u, \gamma)$ be the supply function. 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

$$\rho \equiv \frac{dp}{d\tau} = \frac{S_\tau(p, \tau; u, \gamma)}{D_p(p; \epsilon) - S_p(p, \tau; u, \gamma)}. \tag{3.1}$$

As it is clear from the above equation, the pass-through rate depends on the slope of the demand and supply functions, and on the opportunity costs of permits, as captured by the parameter γ.

Suppose that one has accurately estimated the pass-through rate ρ to be below one. The relevant question would then be how to interpret such an estimate. There is a common misconception that an incomplete pass-through, i.e. $\rho < 1$, goes hands in hands with either market power or lack of cost internalization. However, this is flawed as a general statement. Indeed, $\rho = 1$ is achieved in competitive markets if firms fully internalize emissions costs, but only if demand is vertical or supply is flat.[24] Demand and supply elasticity - and not only market power or partial cost internalization - can lead to partial pass-through, as shown graphically through three examples in Figure 3.1.

In example (a), firms are assumed to be competitive, with linearly increasing marginal costs. Since demand is also upward-sloping, the pass-through rate is less than one. In example (b), firms have constant marginal costs. Since they exercise market power, supply becomes upward-sloping supply,[25] and the pass-through rate is also less than one. Last, in example (c), firms are assumed

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[23]For the sake of simplicity, in this example we assume that the emissions rate is constant in output. In reality, this need not be the case given that different technologies have different emissions rates. This will be relaxed in our empirical analysis.

[24]Under inelastic demand, 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 increase in the permit price is fully passed-through to output prices. Under perfectly elastic supply, ρ in equation (3.1) is undefined as $S_\tau(p, \tau; u, \gamma) = -S_p(p, \tau; u, \gamma) \to \infty$. To solve this indeterminacy, let's parametrize costs as $C(Q) = Q^\alpha$. Now, as $\alpha \to 1$, so that marginal costs become constant, $S_{\tau\alpha} = -S_{p\alpha}$ and $D_{p\alpha} = 0$, so that $\rho \to 1$.

[25]This is consistent with many oligopoly models, including Cournot or the multi-unit auction model, in which markups are increasing in output.

Figure 3.1: An incomplete pass-through is consistent with several hypothesis
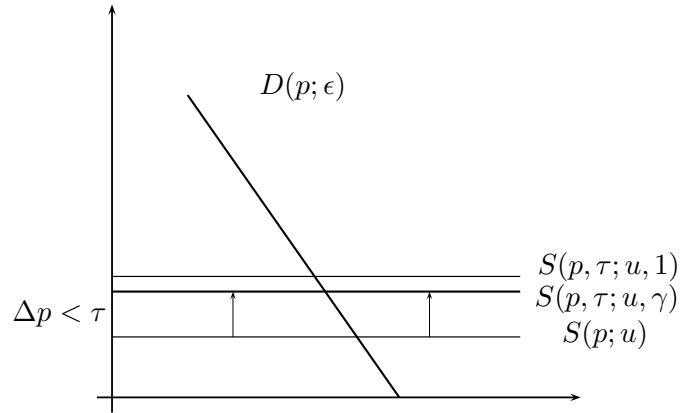
(a) An incomplete pass-through is consistent with competitive behavior when both demand and supply are elastic
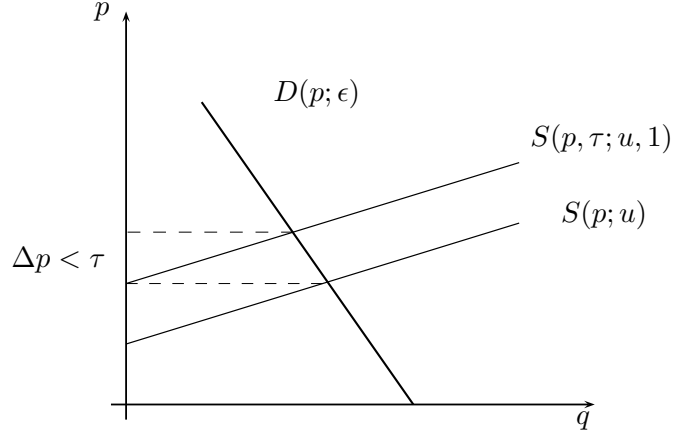
(b) An incomplete pass-through is consistent with market power
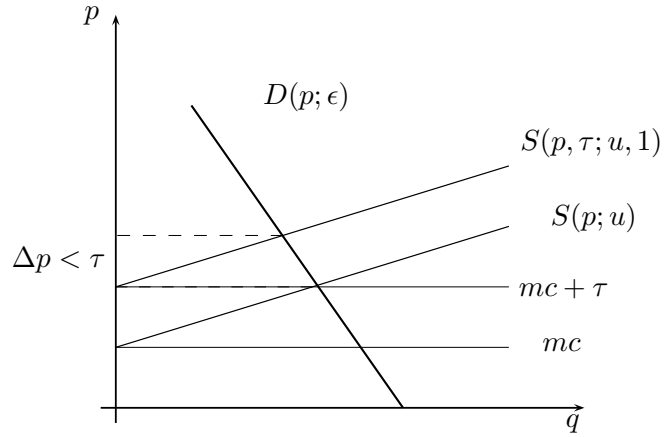
(c) An incomplete pass-through is consistent with partial internalization of emissions costs

to be competitive and their marginal costs are flat. In this case, partial pass-through is explained by partial cost internalization.

In sum, the actual observed pass-through is potentially a combination of three different factors: the elasticity of demand, the elasticity of supply - which in turn depends on cost features as well as on the degree of market power-, and the value of opportunity costs.[26] We now move to empirically quantifying and decomposing the pass-through rate.

4 Reduced-form Evidence on the Pass-through

We first present reduced form evidence on the pass-through rate of emissions costs in the Spanish electricity market. We follow the conventional approach of estimating the pass-through rate by regressing the wholesale electricity price on the emissions permit price. In our particular application, given that there is substantial variation in CO_2 prices, one can identify the pass-through from observed electricity price responses. The main identifying assumption behind the reduced-form 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.

Since different generation technologies have different emissions rates, an increase in the CO_2 price has a different impact on their emissions costs. For this reason, we provide two measures for the pass-through, depending on whether we condition on the emissions rate of the marginal technology, or not. The *cost pass-through* measures the effect on electricity prices of a one euro increase in the marginal cost of the unit setting the price. The *price pass-through* measures the effect of a one euro increase in the CO_2 price on the electricity price.[27]

These two measures are tightly related to each other, but emphasize two different aspects. The price pass-through emphasizes the market impact of the policy, as it is a measure of electricity price increases due to the introduction of emissions permits. 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, and can shed light on issues such as demand response, cost heterogeneity and market power.

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[26]In Section 4.2, we shall add an additional channel that is specific to electricity markets, which we refer to as "Heterogeneity and technology switching." The intuition is that, everything else constant, one can obtain a pass-through rate different from one if the cost shock changes the identity of the price-setting unit, and the marginal emissions rate changes accordingly.

[27]As explained in Section 2, CCGTs and coal plants in the Spanish market have an average emissions rate of 0.35 and 0.95 tons/MWh, respectively. Hence, a CO_2 price of e.g. 10€/ton increases their costs by 3.5€/MWh and 9.5€/MWh, respectively. Accordingly, if the electricity price, set by a CCGT, rises by 3.5€/MWh, the cost pass-through is 100%, while the price pass-through is 35%. If the electricity price is instead set by a coal plant and it rises by 9.5€/MWh, the cost pass-through remains at 100%, while the price pass-through is 95%.

4.1 Price pass-through

To identify the effect of changes in CO_2 prices on electricity prices, we run the following baseline regression:

$$p_{th} = \rho\tau_t + X_{th}\beta_0 + Z_{th}^S\beta_1 + Z_{th}^D\beta_2 + \omega_{th}\delta + \epsilon_{th}, \tag{4.1}$$

where

$$
\begin{aligned}
p_{th} &= \text{hourly electricity price,} \\
\tau_t &= \text{daily cost of the } CO_2 \text{ allowances,} \\
X_{th} &= \text{common controls,} \\
Z_{th}^S &= \text{supply-side exogenous shifters and controls,} \\
Z_{th}^D &= \text{demand-side exogenous shifters and controls,} \\
\omega_{th} &= \text{time fixed-effects (hour, day of week, month and year).}
\end{aligned}
$$

where ρ is our parameter of interest as it identifies the equilibrium price pass-through. Strategies to recover the cost pass-through are discussed in Section 4.2 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 fixed effects to be different for every month, depending on the specification. 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 economic activity indicators[28] and weather, allowing temperature and wind to have a different effect on price depending on the month (for example, a warm day in the winter, which tends to reduce electricity consumption, is very different to a warm day in the summer). On the supply side, we also include controls for renewable capacity and renewable output, which are exogenously given in the short run.

Table 4.1 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 0.44 to 1.17.

The raw relationship between electricity prices and carbon prices is 1.17, as the result of just regressing electricity prices on carbon prices. Specification (1) includes 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, and coal, gas and oil prices.[29] The price pass-through is close to 1.1.

Specification (1) 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 CO_2 prices. To further address this concern, we include month of sample fixed effects. The results change substantially. In specification (2) to (6), we find that the estimated pass-through is between

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[28]Economic activity indicators include a production index provided by the Spanish government and quarterly growth rates in Spain.

[29]The 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.

Table 4.1: Reduced-form **price pass-through** measures

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

	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
τ_t (ρ)	1.108	0.576	0.412	0.471	0.440	0.440
	(0.028)	(0.057)	(0.099)	(0.099)	(0.100)	(0.085)
Obs.	30,648	30,648	18,960	18,960	18,960	18,960
Year-Month FE	N	Y	Y	Y	Y	Y
RD Excluded	N	N	Y	Y	Y	Y
MonthXTemp FE	N	N	N	Y	Y	Y
MonthXWind FE	N	N	N	N	Y	Y
Month-Hour FE	N	N	N	N	N	Y

Notes: Sample from January 2004 to June 2007, includes all thermal units in the Spanish electricity market. All specifications include year, month, weekday, hour and RD fixed effects, as well as weather and demand controls (temperature, maximum temperature, average daily temperature, humidity, holiday index, activity index and Spanish GDP growth rate), supply controls (wind speed and renewable output); and common controls (linear and quadratic commodity prices of coal, gas, fuel oil and brent). Robust standard errors in parentheses.

41% and 57%, depending on the controls included. These more complete specifications seem to line up best with our simulated estimates, reported in Section 5.

4.2 Cost pass-through

The *cost pass-through* measures the effect on electricity prices of increases in the marginal emissions cost (i.e., the price of emissions times the emissions rate of the marginal unit). The baseline regression to identify the cost pass-through is very similar to the price pass-through regression, but we now use the marginal emissions cost instead of the emissions price only:

$$p_{th} = \rho^c\tau_t e_{jt} + X_{th}\beta_0 + Z_{th}^S\beta_1 + Z_{th}^D\beta_2 + \omega_{th}\delta + \epsilon_{th}, \tag{4.2}$$

where ρ^c is our parameter of interest as it identifies the equilibrium cost pass-through. The covariates and controls included are the same as in the price pass-through regression.

To estimate this equation, we need to construct a measure of the marginal emissions rate, e_{jt}. Whenever available, we use the emissions rate of the unit that exactly sets the price. However, there are several hours in which the price-setting unit is not a thermal unit, e.g. when the price is set by a hydro unit. At the margin, hydro units raise the price up to the cost of the thermal unit that would otherwise have been marginal. We therefore use an average of the emissions rates of the thermal units with price offers close to the market price.[30] Finally, there are a few observations for

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[30]In particular, we use observations that fall within 50 cents €/MWh above or below the market price. We have

which we cannot find a thermal unit close to the market price, but for which the Market Operator specifies the marginal technology to be either coal or gas. We thus attribute an emissions rate of 0.95 when coal is said to be at the margin and an emissions rate of 0.35 for CCGT. Overall, we can complete the marginal emissions rate for about 90% of the hours in our sample.[31]

One could be tempted to run the above regression using the marginal emissions rate. However, this measure is likely to be endogenous as the identity of the marginal unit is affected by exogenous cost and demand shocks, which also affect the price. Because of this endogeneity problem, we find negative cost pass-through rates, ranging from -0.17 to -0.22. The basic intuition is that gas tends to set the price when supply is scarce or demand is higher. However, gas has a lower emissions rate, which generates the negative slope. We thus run the above regression after instrumenting the marginal emissions cost, $\tau_t e_{jt}$, with the carbon price itself.

Table 4.2 presents estimates of the cost pass-through rate. All specifications include the most complete set of controls used in the price pass-through regressions, plus various combinations of additional fixed effects. Similar to the price pass-through regression, results for the cost pass-through rate change depending on the number of controls included. In particular, we find the set of month of sample fixed effects to matter the most. When we control for month of the sample in specifications (2)-(6), we find that the cost pass-through rate is around 80%, whereas it is above 100% without the controls.

To explore whether the cost pass-through differs depending on the marginal technology, we interact the emissions cost with a dummy indicating whether coal or gas sets the price at that hour, based on the Market Operator data mentioned above. Given that the Market Operator does not necessarily classify all hours as Coal or CCGT only, to complete all observations, we construct 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 storage is reported marginal at 3am, we consider that coal is at the margin also at 3am. We allow the coefficients on input prices (coal, gas, brent) to change depending on which technology is at the margin.[32]

This approach raises some concerns. First, there remains some heterogeneity in emissions rates among coal plants or among gas plants, which can still cause selection within each group. To avoid this problem, we instrument the emissions cost of the marginal unit with the emissions cost of the marginal technology, as reported by the Market Operator.

Second, results from these regressions may be biased if the separation between hours in which coal or gas sets the price are endogenous to the emissions costs or other factors evolving endogenously with the policy change.[33] There are several reasons to believe this could be a concern. For example, with higher emissions prices, natural gas becomes more competitive and can start substi-

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experimented with 25 cents, 1€ and 2.5€, and the overall results do not change significantly.

[31]There are still a few remaining hours in which we do not observe a thermal unit near the market price and the Market Operator reports other types of units at the margin (hydro, pumped storage, international exchanges, etc.)

[32]Instead, we could have separated the sample in two. We present the results with a split sample in the appendix, which are similar to those reported here.

[33]This would not be corrected even if we split the sample in two. The only situation in which a split sample would correct the selection is if hours in which coal or gas set the price could be exogenously predetermined.

Table 4.2: Reduced-form **cost pass-through** measures

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

	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
$\tau_t e_{jt}$ (ρ^c)	1.587	0.944	0.783	0.832	0.832	0.819
	(0.051)	(0.096)	(0.180)	(0.180)	(0.187)	(0.174)
Obs.	27,530	27,530	16,902	16,902	16,902	16,902
Year-Month FE	N	Y	Y	Y	Y	Y
RD Excluded	N	N	Y	Y	Y	Y
MonthXTemp FE	N	N	N	Y	Y	Y
MonthXWind FE	N	N	N	N	Y	Y
Month-Hour FE	N	N	N	N	N	Y

Notes: Sample from January 2004 to June 2007, includes all thermal units in the Spanish electricity market. All specifications include year, month, weekday, hour and RD fixed effects, as well as weather and demand controls (temperature, maximum temperature, humidity, holdiay index, activity index and Spanish GDP growth rate), supply controls (wind speed and renewable output); and common controls (linear and quadratic commodity prices of coal, gas, fuel oil and brent). The marginal emissions cost is instrumented with the emissions price. Robust standard errors in parentheses.

tuting coal at base load hours. Similarly, coal plants can more frequently appear to be marginal at peak hours, as they become less profitable due to higher emissions costs.

This bias is illustrated in Figure 4.1. The red and black lines respectively represent electricity prices with and without CO_2 prices: coal is cheaper than gas without CO_2, but the ranking reverses once CO_2 prices are taken into account. For the high demand realization depicted in the figure, the marginal unit with CO_2 is coal, though it would have been gas without CO_2. Given that the emissions rate of coal is higher, one would then tend to underestimate the pass-through rate, as one would expect a price change A, instead of the observed change B < A. The opposite holds for the low demand realization, when the marginal unit with CO_2 is gas. One would now tend to overestimate the pass-through, as one would expect a price change C instead of the actual price change D > C.

Table 4.3 presents estimates of the cost pass-through rates depending on whether coal or gas are at the margin. When we control for month of the sample in specifications (2)-(6), we find that the cost pass-through when coal is at the margin is lower than when gas is at the margin. In particular, under specification (6), estimates are 63% and 93% respectively, which lay below and above the estimated 82% reported in Table 4.2. Therefore, this difference, even though not statistically significant, is consistent with technology substitution taking place, as illustrated in Figure 4.1.

The reduced-form approach is informative, but it faces some limitations. As we have discussed, estimates are noisy and not fully robust to the different specifications: first, it is difficult to obtain a

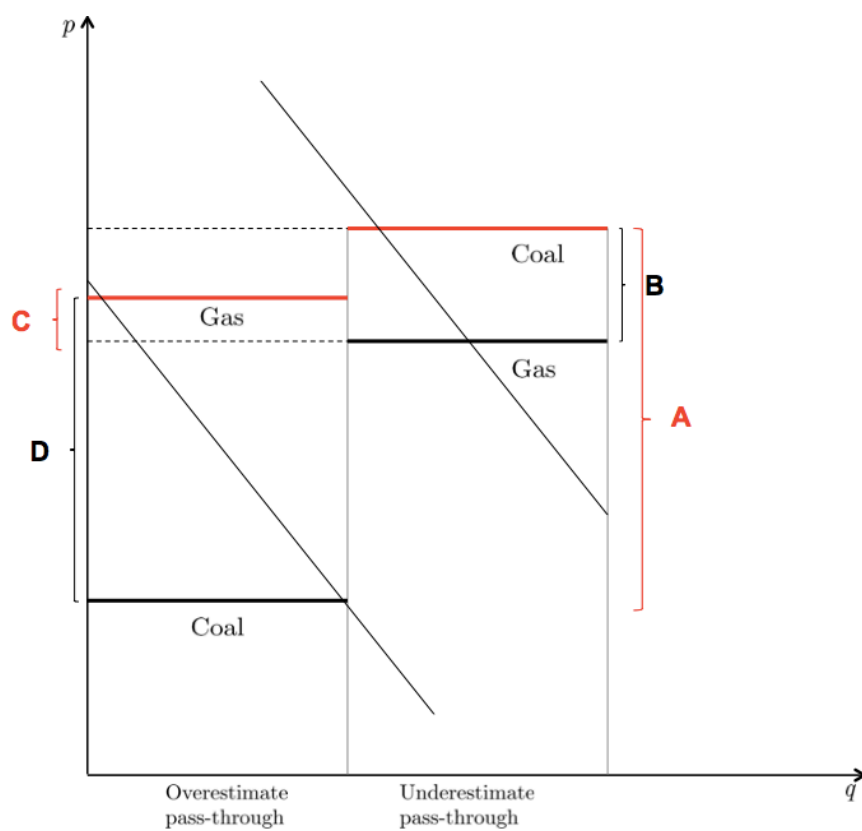**Figure 4.1:** Estimating cost pass-through with heterogeneous cost shocks

Table 4.3: Reduced-form **cost pass-through** measures by technology groups

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

	(1)	(2)	(3)	(4)	(5)	(6)
$e_{jt}\tau_t$ $(\rho^{c,Coal})$	1.114	0.591	0.665	0.664	0.658	0.637
	(0.119)	(0.199)	(0.447)	(0.439)	(0.446)	(0.412)
$e_{jt}\tau_t$ $(\rho^{c,CCGT})$	1.998	1.025	0.780	0.862	0.881	0.933
	(0.067)	(0.126)	(0.276)	(0.272)	(0.277)	(0.254)
Obs.	27,530	27,530	16,902	16,902	16,902	16,902
Year-Month FE	N	Y	Y	Y	Y	Y
RD Excluded	N	N	Y	Y	Y	Y
MonthXTemp FE	N	N	N	Y	Y	Y
MonthXWind FE	N	N	N	N	Y	Y
Month-Hour FE	N	N	N	N	N	Y

Notes: Sample from January 2004 to June 2007, includes all thermal units in the Spanish electricity market. All specifications include year, month, weekday, hour and RD fixed effects, as well as weather and demand controls (temperature, maximum temperature, humidity, holdiay index, activity index and Spanish GDP growth rate), supply controls (wind speed and renewable output); and common controls (linear and quadratic commodity prices of coal, gas, fuel oil and brent). Input controls (oil, coal, gas) are allowed to depend by technology group. The marginal emissions cost is instrumented with the emissions price interacted with the technology group dummy. Robust standard errors in parentheses.

clean identification with time-series variation only; and second, one would expect several variables affecting demand or supply to be correlated with the CO_2 prices (e.g. growth rates, exchange rates, fossil-fuel prices, etc.), so that estimates might suffer from a omitted variables bias. Furthermore, even if the pass-through is accurately estimated, this approach does not allow us to disentangle all the channels that generate the estimated pass-through. These shortcomings call for a more structural approach, which we develop next.

5 Structural Decomposition of the Pass-through

In this section, we rely on a structural bidding model with a two-fold objective. First, we use the model to identify the value of firms' perceived opportunity costs of using emissions permits. This is a necessary first step for quantifying the pass-through rate, as if e.g. the opportunity cost of permits was lower than the permit price, our pass-through estimate would be underestimated. Second, we use the model to simulate the response of firms' pricing behavior to marginal changes in the carbon price. This allows us to identify the role of demand response, market power and technology switching in explaining the simulated pass-through estimates.

5.1 Bidding Model

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 opportunity costs of using permits, $\gamma_i \tau e_i Q_i^S$, where γ_i is firm i's "opportunity cost" parameter, τ is the permit price, and e_i is firm i's emissions rate.[34]

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 to cover its retail sales.[35]

We can write firm i's profits in the day-ahead market as follows:[36]

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

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[34] For simplicity, we omit here the fact that firm i might have different units with different emissions rates. Since our estimating equation relies on the the First Order Condition, we will only be concerned about the emissions rate of firm i's marginal unit, which we will denote by e_{ij}.

[35] In principle, retailers are allowed to submit downward sloping demand functions. Nonetheless, 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.

[36] We 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) for profit maximization must be satisfied for firm i.[37] Solving the FOC for p,

$$p = c_i + \gamma_i \tau e_i + \left| \frac{\partial D_i^R}{\partial p} \right|^{-1} Q_i, \tag{5.1}$$

where c_i denotes the marginal production cost at Q_i^S, and $Q_i = Q_i^S - Q_i^D$ denotes the firm's net production.

All of the fundamentals in equation (5.1) are observed in the bidding data or they can be appropriately simulated, except for the parameter γ_i. For this reason, we first infer the value of γ_i from the bidding data using the optimal bidding equations. Next, we estimate the pass-through rate by simulating how firms' bidding functions would change in response to marginal changes in CO_2 prices around the equilibrium price.

5.2 Estimating Opportunity Costs

Under the assumption of profit-maximizing behavior, we infer the value of firms' opportunity costs of using permits from the bids submitted in the day-ahead market.

Based on the optimal bidding condition (5.1), we estimate the following empirical equation in those hours in which firm i is setting the market price through its marginal unit j:

$$b_{ijth} = \alpha_{ij} + \beta_i c_{jt} + \gamma_i \tau_t e_{ij} + \left| \frac{\widehat{\partial D^R}_{ith}}{\partial p_{th}} \right|^{-1} Q_{ith} + \epsilon_{ijth},$$

where

b_{ijth}	$=$	marginal bid by firm i when setting the price with unit j, hour h and day t,
α_{ij}	$=$	unit j fixed-effect,
c_{ijt}	$=$	marginal costs of marginal unit j,
e_{ij}	$=$	emissions rate of the marginal unit,
τ_t	$=$	daily cost of the CO_2 allowances,
$\frac{\widehat{\partial D^R}_{ith}}{\partial p_{th}}$	$=$	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, modeling error and/or firm optimization error).

The parameters to be estimated are $\Theta = \{\alpha_{ij}, \beta_i, \gamma_i\}$. Testing that the permit price fully reflects the opportunity costs of using permits involves testing $\gamma_i = 1$, which is the focus of our discussion below. Some of the elements in the above specification are readily observed, such as the emissions rate of the marginal unit and carbon prices. We construct the inframarginal quantity variable taking into account all offers made by a firm, including both supply and demand units.

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[37] As 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.

Table 5.1: Test based on structural equations

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

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

Furthermore, given that we have fine level data on hourly demand and supply functions, we can construct the 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. To the extent that other costs might not be accurately reflected into this variable, we also introduce unit fixed effects.[38]

Table 5.1 presents the structural estimates of the opportunity costs parameter. The estimations are performed at the industry level and at the firm level. All specifications include marginal cost estimates as controls. The first three specifications differ on whether we introduce unit fixed effects and seasonal fixed effects. The fourth specification excludes those dates when the Royal Decree (RD) was in place. Last, in the fifth specification we instrument the markup component, $\left| \frac{\partial \widehat{D^R}_{ith}}{\partial p_{th}} \right|^{-1} Q_{ith}$. Given that the markup depends on market demand, we use residual demand shifters, including weather data (temperature, wind speed, humidity), economic activity data, and renewable production, all of which are exogenous to firms' choices.

The estimated opportunity cost parameter is close to one for the industry as a whole and for firm 1, which is the largest firm in the market. This also true for firm 2, the second largest firm, except for specifications (2) and (3). It has been documented that firm 2 followed an anomalous bidding behavior under Royal Decree 3/2006,[39] thus suggesting that the estimates might be biased when we include this period in the sample. The parameter estimated for the two other firms is also

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[38]Results are also robust to allowing the marginal cost coefficient to be unit-specific.

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

close to one, 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 plants with less variation in marginal costs and emissions rates, making the identification more sensitive to the controls and the included sample.[40]

Finally, Table A.2 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. Results are similar, overall providing evidence consistent with the hypothesis that firms perceived the CO_2 price as the relevant opportunity cost of emissions.

As a robustness check, we extend the analysis of Reguant and Ellerman (2008).[41] The approach relies only on observing on/off patterns by power plants, and testing whether those decisions respond equally (though with opposite sign) to changes in the market price as to changes in their marginal emissions cost. As reported in Table A.3 in the appendix, the results support the hypothesis of full internalization across a wide range of specifications.

Overall, our evidence is consistent with the hypothesis of full cost internalization of the price of emissions permits.

5.3   Simulating Pass-through Channels

As presented in section 5.2, the equilibrium bidding equations at the wholesale electricity auction are given by,

$$b_{ijth} = \alpha_{ij} + \beta_j c_{jt} + \tau_t e_{ij} + \Big|\frac{\partial \widehat{D^R}_{ith}}{\partial p_{th}}\Big|^{-1} Q_{ith} + \epsilon_{ijth}, \tag{5.2}$$

where, given the previous evidence, we have assumed that the permit price reflects the true opportunity costs of emissions, i.e. $\gamma_i = 1$.

We use these optimal bidding equations to simulate how firms' bidding functions would change in response to marginal changes in CO_2 prices. In particular, we compute the counterfactual in which the cost of emissions increases by one euro, i.e. $\tau' = \tau + 1$, and then compute the implied pass-through rates.[42] Since the change in emissions costs is small, we can safely take participation decisions as given.[43]

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[40]The identification is potentially improved in Table A.2 in the Appendix, as it relies on an expanded data set. The parameter estimated for the third firm is approximately equal to one, while that for the fourth firm, which is the smallest firm in the market, remains below one.

[41]See Reguant and Ellerman (2008) for details on this test. The study was focused on coal units. We extend the analysis to all thermal technologies affected by the EU ETS.

[42]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 of setting the price and therefore reflect the marginal incentives faced by the firm.

[43]Characterizing the optimal startup decision is beyond the scope of this paper. See Reguant (2012) for a computation of optimal strategies in the presence of startup 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.

As shown in equation (5.2), an increase in carbon prices can affect optimal bids in two ways. First, it affects marginal costs directly, through the $\tau_t e_{ij}$ component. Second, if firms are strategic, the carbon price increase can affect the markup component by changing the shape of the residual demand as well as the firm's net inframarginal production.

To the extent that the cost shock changes equilibrium bidding by some units, it might also affect the bidding behavior of units that do not face the cost shock, particularly hydro units. To account for the opportunity costs of hydro units,[44] we assume that they would modify their bids in the same manner as the neighboring units on the aggregate supply function, so that their relative strategic position in the merit order would not change.[45]

Table 5.2 represents a matrix of the counterfactuals we consider. To separate demand and supply channels that affect the pass-through, we first compute counterfactual I in which we hold demand fixed and change bids in a competitive fashion.[46] In these simulations, the only change is an increase in bids corresponding to a one euro increase in permit costs, i.e., bids go up by e_{ij}. Second, in counterfactual II, we allow for demand response by incorporating the actual demand curve in the market.[47]

Counterfactuals III and IV are analogous to the first two, but we allow the markup component to endogenously 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.

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 substantial.[48] We then update prices for all firms under the new markups and examine the impact on the electricity market price. With this approach, we intend to capture some of the changes in markups that result from an increase in emissions costs.

Heterogeneity and technology switching Counterfactual I is very useful to provide an intuition behind the pass-through distribution that we observe in the data. With inelastic demand, the cost pass-through should equal one unless the cost shock changes the merit order in the underlying supply curve. Therefore, any departures from one must be due to technology switching.

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[44]Hydro plants can store the water in their reservoirs to use it in a different period. Hence, their opportunity costs is given by the revenue the firm could make by selling its hydro production in a different period. As prices in other periods are likely to be affected by the increase in emissions costs, the opportunity costs of hydro plants are likely to be affected too.

[45]Admittedly, this is an ad-hoc way to capture the change in hydro bids. Modeling the dynamic decision of hydro is beyond the scope of this paper. An alternative procedure 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).

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

[47]Note 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.

[48]Wolak (2007) follows the same approach, among others. Ideally, one would like to compute the new equilibrium price given the cost shock. However, computing the new equilibrium with more than one firm requires developing a more explicit computational model that does not rely on FOC only, and it does not necessarily address the concerns of multiple equilibria. See Reguant (2012) for a discussion.

Table 5.2: Simulated Bids and Pass-through Counterfactuals

I Inelastic Demand Only MC Change	II Demand Response Only MC Change
III. Inelastic Demand MC + Markup Change	IV. Demand Response MC + Markup Change

Figure 5.1: Distribution of cost pass-through rates
with inelastic demand and observed bids
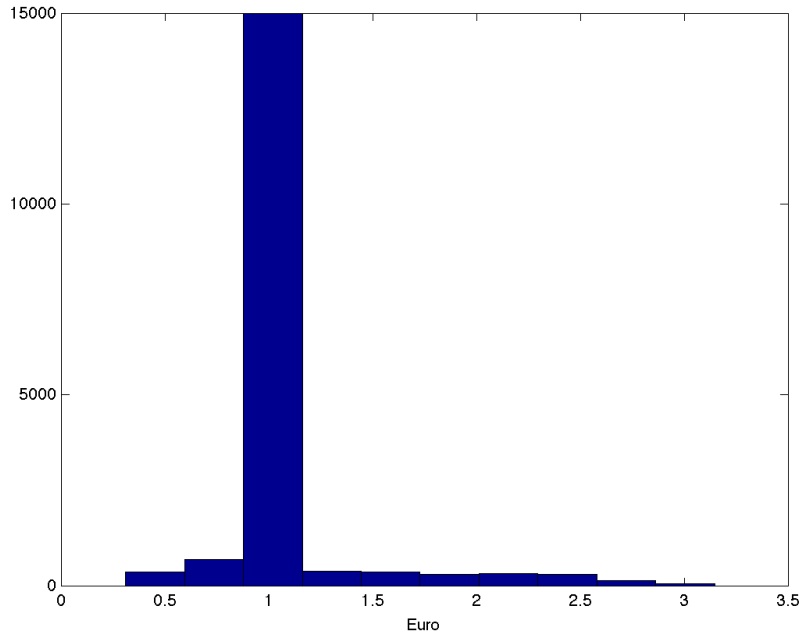
The histogram represents the effect of a one euro increase in the marginal costs of the marginal technology on the electricity price. The sample is restricted to hours in which the marginal unit has a positive emissions rate.

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 in most observations the pass-through is one, we see some departures, which occur when there is substitution away from coal to gas (recall Figure 4.1).

The role of technology switching and market power   Given relative prices for coal and gas during the sample period, and the relatively low CO_2 prices during part the sample, one would expect to observe little technology switching in a competitive setting. Hence, there remains the question of whether the observed cost pass-through reflects cost heterogeneity or whether it is consistent with the exercise of market power. In particular, if there are big strategic firms that have a particular generation mix (coal and gas), and fringe players that only have gas, one would expect to see more substitution under the actual merit order than in a competitive setting. Accordingly, differences in technology switching across counterfactuals reflect production inefficiencies that could be attributed to market power.[49]

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, instead of using observed bids, we use the industry competitive supply function, i.e., taking engineering cost estimates. The results of this counterfactual are presented in the first block of table 5.3, which summarizes our results. We find that the competitive pass-through rate is also one in most cases, although it presents less variance than the strategic one (standard deviations are 0.226 *vs.* 0.335).

Indeed, under the competitive benchmark, departures in full cost pass-through rates due to technology switching occur only in 12.35% of the hours of the sample.[50] In contrast, technology switches occur in 19.06% of the hours using observed bids.[51,52] These results suggest that the observed departures from full cost pass-through reflect technology switching generated by differences in strategic bidding behavior across firms.[53]

The role of demand elasticity and supply elasticity   Counterfactual II introduces demand elasticity, as implied by the observed wholesale demand curves. Results are presented for the cost

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

[50]We define departures from full pass-through if the pass-through is not between 95%-105% to avoid counting small fluctuations. Other definitions are also consistent with these differences, although the percents are larger across the board as the definition gets narrower.

[51]If 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 (6.86% vs 10.69%, respectively).

[52]Related to these switching measures, we can also quantify whether the departures from full pass-through are due to the marginal unit switching from coal to gas or the opposite. For the strategic case, switching occurs from coal to gas in 6.60% of the hours, whereas it occurs 12.46% from gas to coal. At peak hours, there is also more substitution from gas to coal at the margin (3.73% from coal to gas versus 6.95% from gas to coal), consistent with Figure 4.1.

[53]Even though this is suggestive evidence that coal and gas are more mixed in the observed data than in the competitive supply curve, one needs to keep in mind the possibility that our engineering cost measure is missing some of the actual heterogeneity across plants.

Table 5.3: Pass-through (PT) Results

		Cost Pass-through		Price pass-through	
		Inelastic	Elastic	Inelastic	Elastic
Competitive	Mean	1.034	0.842	0.706	0.561
	Median	1.000	1.000	0.716	0.580
	St.Dev.	(0.226)	(1.021)	(0.286)	(0.642)
Only MC Change	Mean	1.080	0.774	0.695	0.484
	Median	1.000	1.000	0.739	0.416
	St.Dev.	(0.335)	(0.747)	(0.275)	(0.466)
MC + Markup Change	Mean	1.099	0.778	0.697	0.479
	Median	1.000	1.000	0.715	0.415
	St.Dev.	(1.504)	(1.588)	(0.751)	(0.807)

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.

and price pass-through in the second and fourth column of Table 5.3, respectively. As can be seen, introducing demand response reduces the cost pass-through to around 84% on average for the competitive benchmark, and to 77% using actual bid data. The fact that the cost pass-through is lower in the strategic case is consistent with the supply curve being less elastic in the presence of strategic firms.

Looking at the market price effects, we find that the average price pass-through is around 70% when we consider only changes in marginal costs under inelastic demand. Introducing demand response at the wholesale auction decreases price pass-through substantially, to around 50%. In both cases, the average price pass-through lies between the emissions rate of gas (approx. 35%) and coal units (approx. 95%).

The role of markup changes Finally, we repeat all counterfactuals allowing the markups to change strategically. As seen in the last set of results of Table 5.3, this has a relatively minor impact on the average pass-through, as well as on the relative differences across counterfactuals, although it increases the variance.

To visually summarize all the results, Figure 5.2 presents a graphical decomposition for the case in which we only modify bids by adding the increase in emissions costs. In sum, we find that demand response and market power reduce the cost pass-through. The analogue for the case in which we distort markups is relegated to the appendix. As it becomes apparent, the partial pass-through is both a combination of demand elasticity and market power.

Combining the reduced form evidence with the structural approach, we find intermediate levels of price pass-through (around $40-60\%$) and levels of cost pass-through close to 80%. The simulated results suggest there is scope for an attenuated cost pass-though due to demand response and market

Figure 5.2: Comparison of pass-through rates across counterfactuals
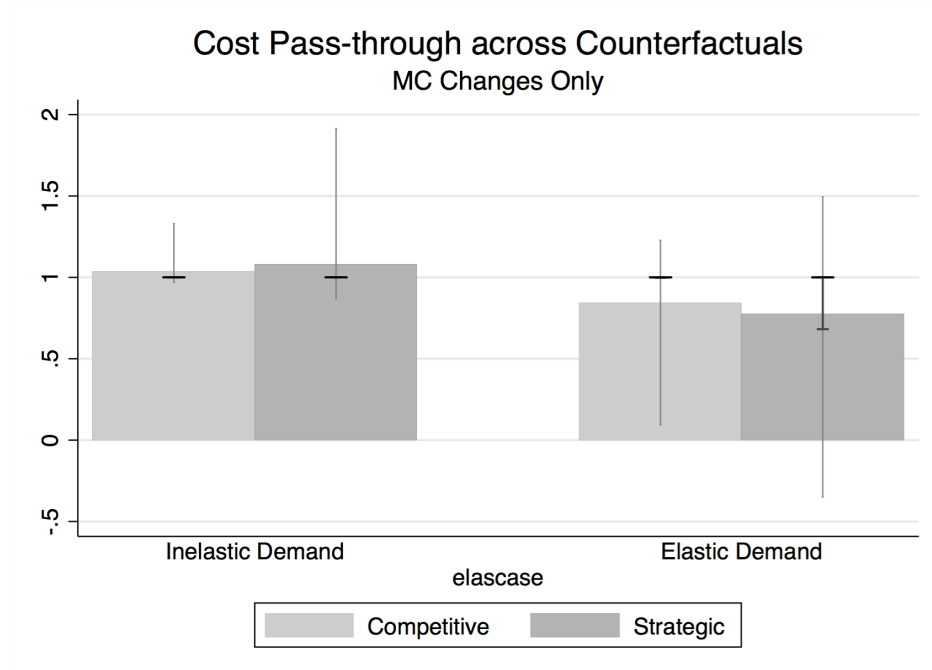
Note: The solid bars represent the average cost pass-through. The black marker represents the median, the dark gray brackets represent the interrange quantile and the light gray line represents the 5 and 95 percentile.

power. Also, both the reduced-form approach and the simulations reflect substitution between coal and gas, which appears to be less frequent in the competitive counterfactual.

6 Conclusions

We have presented an empirical assessment of the effect of emissions permits in the Spanish electricity market. In particular, we have quantified the pass-through of the cost of permits to electricity prices and decomposed the channels that generate it. The analysis has benefited from the richness of the micro-level data, which has allowed us to perform structural estimations without imposing strong assumptions on the shape of demand or supply.

The empirical results support the hypothesis that firms internalize the full cost of emissions in this market, specially the big firms. With inelastic demand and homogeneous technologies, this would have translated into cost pass-through rates close to one. However, as a consequence of demand response and market power, estimated cost-pass-through rates fall to 80% on average. This incomplete pass-through is also reflective of the substitution from dirtier (coal) to cleaner (gas) plants, which tends to be more pronounced than under a competitive setting given differences in strategic bidding behavior among firms. The implied effects on price are around 50%, reflecting the average emissions rate of the marginal technologies. The price pass-through rate would have been 20% higher had it not been for the effect of demand elasticity in the wholesale market.

Our results have several policy-relevant conclusions. First, starting January 2013, full auctioning of emissions permits has become compulsory. As we have shown, the fact that firms internalize 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.[54] Full cost internalization also suggest that frictions or transaction costs in the emissions market are negligible, which as is well known is a necessary condition for the Coase principle to apply. Last, the evidence reported here on the degree of pass-through demonstrates that Spanish electricity generators benefited from the introduction of emissions regulation through increased windfall profits due to free permit allocation and increased market prices.[55]

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. (2013). 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. (2013). Profiting from regulation: evidence from the European carbon market. *American Economic Journal: Economic Policy*.

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 Perthius, 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.

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

[55]For the Netherlands, Sijm et al. (2006) estimate this at 300-600 million € per year, i.e., approx. 3 to 5 €/MWh.

Fowlie, 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. Csem working paper, UC Energy Institute.

Kühn, K.-U. and Machado, M. (2004). Bilateral Market Power and Vertical Integration in The Spanish Electricity Spot Market. Working Paper DP4590, CEPR Discussion Paper.

Marion, J. and Muehlegger, E. (2011). Fuel Tax Incidence and Supply Conditions. Working Paper 16863, National Bureau of Economic Research.

Martin, R., Muuls, M., de Preux, L., and Wagner, U. (2012). Industry compensation under the risk of relocation: A firm-level analysis of the EU emissions trading system.

McGuinness, M. and Ellerman, A. D. (2008). CO_2 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. (2012). 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). CO_2 Cost Pass-Through and Windfall Profits in the Power Sector. *Climate Policy*, 6:49–72.

Stavins, R. (1995). Transaction Costs and Tradable Permits. *Journal of Environmental Economics and Management*, 29:133–148.

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*.

Wolak, F. A. (2007). Quantifying the Supply-Side Benefits from Forward Contracting in Wholesale Electricity Markets. *Journal of Applied Econometrics*, 22:1179–1209.

Wolfram, C. (1999). Measuring Duopoly Power in the British Electricity Spot Market. *American Economic Review*, 89(4):805–826.

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 Tables

Table A.1: Reduced-form **cost pass-through** measures by technology groups

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

	(0)	(1)	(2)	Coal subsample (3)	Coal subsample (4)	CCGT subsample (5)	CCGT subsample (6)
$e_{jt}\tau_t$ $(\rho^{c,Coal})$	-0.095	0.617	0.637	0.762	0.625		
	(0.071)	(0.191)	(0.412)	(0.099)	(0.157)		
$e_{jt}\tau_t$ $(\rho^{c,CCGT})$	0.670	1.095	0.933			1.207	0.964
	(0.036)	(0.121)	(0.254)			(0.147)	(0.288)
Obs.	27,530	27,530	16,902	14,391	10,055	13,139	6,847
Instruments	N	Y	Y	Y	Y	Y	Y
RD Excluded	N	N	Y	N	Y	N	Y
YearXMonth FE	Y	Y	Y	Y	Y	Y	Y

Notes: Sample from January 2004 to June 2007, includes all thermal units in the Spanish electricity market. All specifications include year, month, weekday, hour and RD fixed effects, as well as weather and demand controls (temperature, maximum temperature, humidity, holdiay index, activity index and Spanish GDP growth rate), supply controls (wind speed and renewable output); and common controls (linear and quadratic commodity prices of coal, gas, fuel oil and brent). Input controls (oil, coal, gas) are allowed to depend by technology group when applicable. The marginal emissions cost is instrumented with the emissions price (interacted with the technology group dummy when applicable). Robust standard errors in parentheses.

Table A.2: Test based on structural equations - Bandwidth sensitivity

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

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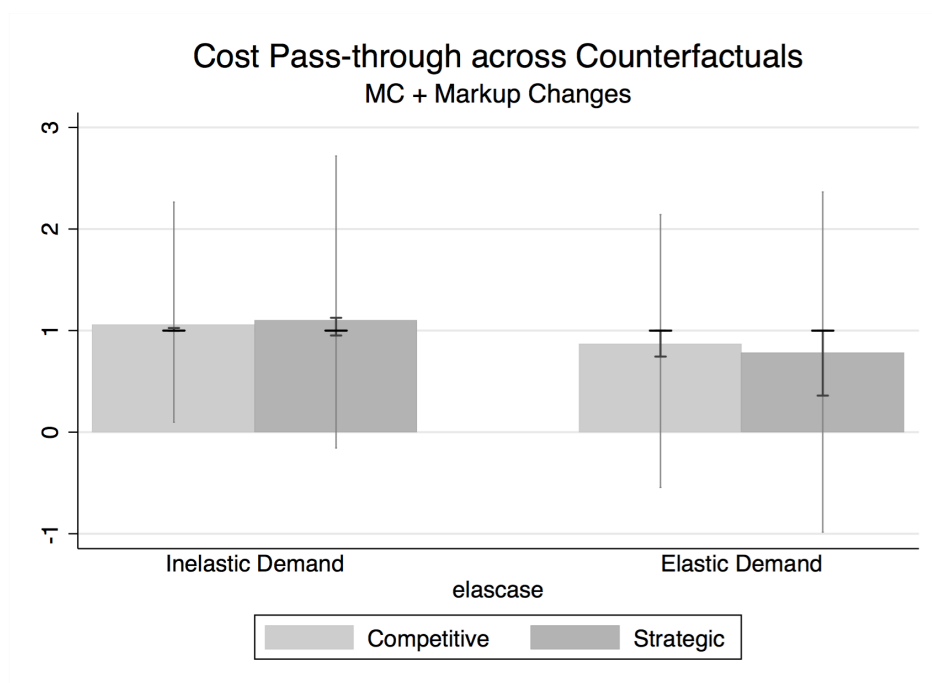
Table A.3: Test based on operational patterns

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

	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
$p_t\ [\beta_1]$	8.766	10.697	5.673	5.668	6.032	5.818	7.198
	(0.607)	(0.937)	(0.917)	(0.916)	(0.938)	(0.927)	(1.126)
$e_i\tau_t\ [\gamma]$	-6.799	-8.423	-6.016	-5.932	-5.302	-5.674	-5.625
	(1.652)	(1.546)	(1.105)	(1.112)	(1.928)	(1.831)	(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 $\text{\euro}10^{-3}$.

Comment: The regression models the on/off decision of a given power plant at a daily level, as in Reguant and Ellerman (2008). The dependent variable is the status of a unit during a given day (on/off). A firm is on if it starts up that day or if it is already producing during the day. Due to the presence of startup costs and dynamic continuation value, it is best to separate those days in which the firm needs to incur startup costs from those in which they are already running. We focus on days in which the units are turned off and are deciding whether to startup or not, as in Fowlie (2010). Similar results obtain if focusing on the sample of units that are already turned on. An array of controls is meant to capture the fixed costs of startup (unit fixed effects), strategic interactions (inframarginal quantity), other aggregate confounding factors (month of sample fixed effects) and variations in continuation value (unit specific weekly fixed effects).

Figure A.1: Comparison of pass-through rates across counterfactuals

Note: The solid bars represent the average cost pass-through. The black marker represents the median, the dark gray brackets represent the interrange quantile and the light gray line represents the 5 and 95 percentile.