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 analyze the factors that generate it: internalization of emissions costs, demand elasticity, market power and heterogeneity of cost shocks. Using rich micro-level data, we perform both reduced form and structural estimations based on optimal bidding in this market. We find that 80% of the emissions cost is passed-through to electricity prices. This incomplete pass-through is partly driven by demand elasticity and market power. Finally, our results are consistent with the hypothesis that firms internalized the full cost of the emissions.

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.[1] 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. If all agents internalize the same price on emissions, i.e., the price of permits in the emissions markets, the lowest abatement cost allocation will be achieved.

However, 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. Their impact on electricity bills is particularly controversial, since electricity markets are strongly affected by the emissions regulation. 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 (Martin et al., 2012). 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 policy debate on the effects of pollution permits on output prices in the context of electricity markets has been the belief that in competitive markets full internalization of permit prices necessarily implies full pass-through (Ellerman et al., 2010).[2] 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 in general. Partial pass-through could be explained by either partial cost internalization, market power, demand elasticity, or any combination between them.

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. To do so, we investigate the response of Spanish electricity firms to the introduction of emissions regulation, taking advantage of the cost shocks induced by changes in emission permits.

We first quantify the pass-through rate through a reduced-form analysis based on observed equilibrium outcomes. Our findings demonstrate that 80% of the increase in emissions costs is passed-through to electricity prices. In turn, this implies that electricity prices increase by approximately half the carbon price. We also find that the pass-through rate is reduced when coal units set the price, while it is exacerbated when gas is the marginal technology. This is consistent with the latter cleaner technology substituting the dirtier one at the margin.

To understand the different channels that explain this incomplete pass-through, we then rely

[1] Under cap-and-trade programs, the total amount of emissions is capped, and emissions permits summing up to the cap are distributed among pollutants. These can then freely trade them in the emissions market or through bilateral trades in order to cover their emissions. The European Union's Emissions Trading Scheme (ETS), currently the largest carbon market in the world, is the European Union's flagship instrument to fight climate change. See Ellerman et al. (2010) for details.

[2] The rationale behind this conclusion is that it would be true under the assumption of perfectly inelastic demand.

on a structural approach based on the predictions of the multi-unit auction literature. To explore whether the 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. Several hypothesis have been put forward to explain why firms might not factor in the full permit price. Explanations include the existence of transaction costs in the emissions market (Stavins, 1995), the expectation that future permit allocations would be based on current emissions (Fowlie, 2010), or firms' inability to understand that free permits have an opportunity cost (Goeree et al., 2010). However, our analysis shows that firms internalized the cost of the permits fully, suggesting that partial pass-through is not explained by partial internalization of emissions costs.

To decompose the additional channels that result in partial pass-through, such as demand elasticity and market power, we simulate the response of firms' bidding behavior to marginal increases in the carbon price. More specifically, we use optimal bidding equations to predict how the whole bid schedule would change after a one Euro increase in the carbon price. We do so under four counterfactuals, which differ on whether demand is elastic or not, and on whether firms' strategic markups are affected by the carbon cost shock or not. In the counterfactual with inelastic demand, we find departures from full pass-through that are solely due to substitution from dirtier (coal) to cleaner (gas) technologies. In turn, the observed switching is more prominent than in the competitive benchmark because of asymmetries in bidding behavior between the large strategic firms and the fringe players. The comparison across counterfactuals also shows that demand elasticity has a significant impact in mitigating the pass-through, which is reduced by 20% as compared to the counterfactuals with inelastic demand.

Our results have several policy-relevant implications. First, in the context of the European Union's Emissions Trading Scheme (ETS) and electricity markets, starting from January 2013, full auctioning of emission permits has become compulsory. 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.Secondly, full cost internalization also suggests that frictions or transaction costs in the emissions market are negligible, which is a well known necessary condition for the Coase principle to apply. Finally, the evidence reported here on the degree of pass-through demonstrates that the introduction of emissions regulation in electricity markets with free permit allocation can be a source of windfall profits due to increased market prices.

This paper also contributes to the general understanding of economic pass-through. The introduction of carbon cap-and-trade in electricity markets provides a unique opportunity to identify the different channels that affect the pass-through. First, 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. Second, 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, since pollution permits are traded across all Member States and across many sectors. Furthermore, there is substantial variation in permit prices during the sample. Studying these markets also has the advantage that there is rich high-frequency micro-level data available, including demand curves and individual firm bid data, as well as engineered-based cost estimates, that allow us to be flexible in the structural simulations.[3] Finally, the institutions and industrial processes that affect firms' strategic behavior in these markets are also well understood (von der Fehr and Harbord (1993) and Green and Newbery (1992), among others), thus allowing us to construct a reliable structural framework.

The paper proceeds as follows. After reviewing the related literature, Section 3 describes the context and data of analysis. In Section 2, 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, the majority of which present reduced-form evidence and do not explicitly explore the channels explaining the pass-through rate. Also, while previous studies on pass-through rates are based on market outcomes, this paper uses finer micro-level data to assess the response by firms more directly.

One of the first papers studying this issue is Sijm et al. (2006), which estimates pass-through rates using equilibrium prices and fuel cost data in the German electricity market.[4] The authors find pass-through rates that range between 0.60 and 1.17, depending on market conditions. More recently, 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.

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) also present evidence that electric utilities in the UK changed their operational decisions in response to carbon prices in the EU ETS, but do not directly assess whether the response is consistent with full internalization.

In the context of other pollution markets, Kolstad and Wolak (2008) provide 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 evidence that firms internalized the costs of emissions, and that the degree of internalization depended on the subsidization rate, as theory would predict.

[3] 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).

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

The relevance of identifying the pass-through rate in the presence of cost shocks extends beyond 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. 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 aims at contributing to this line of research.

2 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 given by

$$TC(Q;\gamma) = C(Q;u) + \gamma\tau eQ. \tag{2.1}$$

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.[5] The common assumption is that the emissions' permit price, τ, fully reflects the opportunity costs of using permits, so that τeQ represents the costs of emissions. However, several features of these markets may distort opportunity costs away from permit prices, e.g., transaction costs in the emissions markets (Stavins, 1995), the belief that future permit allocations would be based on current emissions, behavioral biases that stop firms from fully understanding that free permits have an opportunity cost,[6] or financial market imperfections.[7] In order to capture these possibilities, we introduce a parameter, γ, referred to as the "opportunity costs" parameter, which adjusts for the firm's true opportunity costs of using permits.

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

[5] 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.

[6] This issue that is reminiscent of the concern that auctioning permits will inflate output prices. 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] 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)

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

$$\rho \equiv \frac{dp}{d\tau} = \frac{S_\tau(p, \tau; u, \gamma)}{D_p(p; \epsilon) - S_p(p, \tau; u, \gamma)}. \tag{2.2}$$

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. 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 downward-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 and the pass-through rate is also less than one.[8] Last, in example (c), firms are assumed 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.[9] We now move to empirically quantifying and decomposing the pass-through rate into these three channels.

3 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.

3.1 The European Union's Emissions Trading Scheme

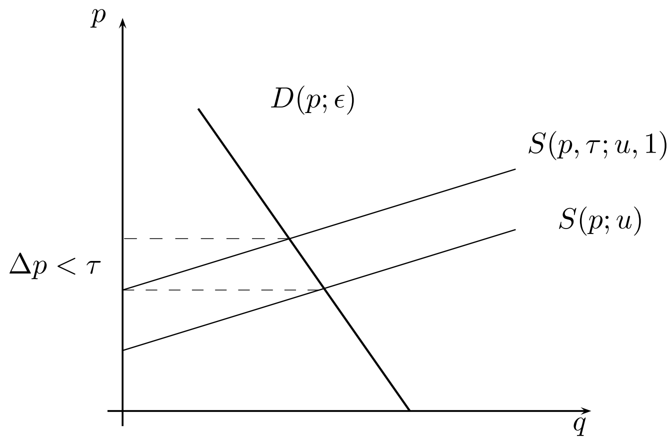
The EU ETS is the largest emissions control scheme in the world, affecting almost half of European CO_2 emissions, from approximately 10,000 energy-intensive installations across the EU. It is also the first and largest compulsory international trading system for CO_2 emissions.

[8] This is consistent with many oligopoly models, including Cournot. As documented in the literature, one could also construct an example in which market power increases the pass-through above one.

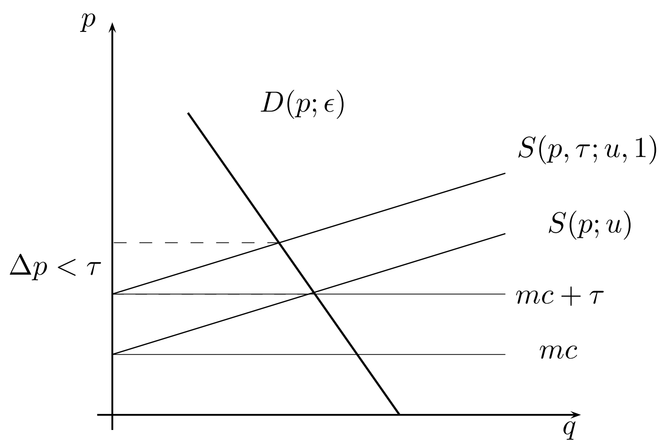
[9] In Section 4.2, we shall add an additional channel that is specific to electricity markets, which we refer to as "heterogeneity and technology switching." Everything else constant, one can obtain a pass-through rate different from one if there is substitution from dirtier to cleaner technologies at the margin.

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

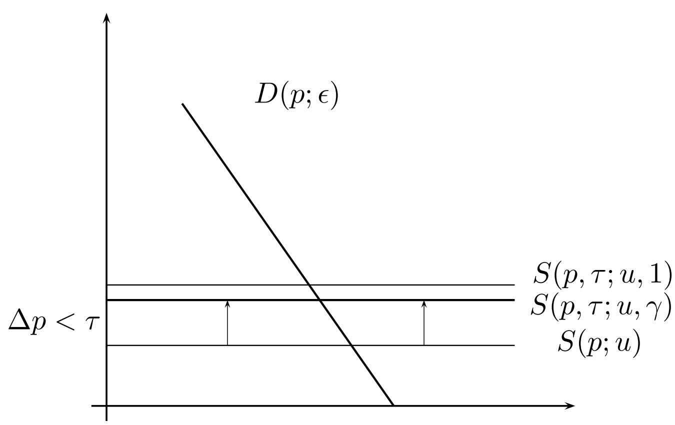
(a) An incomplete pass-through is consistent with competitive behavior when both demand and supply are elastic



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



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



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. 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.[10] 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 (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.[11]

Figure 3.1 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).[12]

3.2 The Spanish Electricity Market

The Spanish electricity market is a national market that produces between 15,000 and 45,000 MWh hourly and serves more than 40 million people. 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. 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.

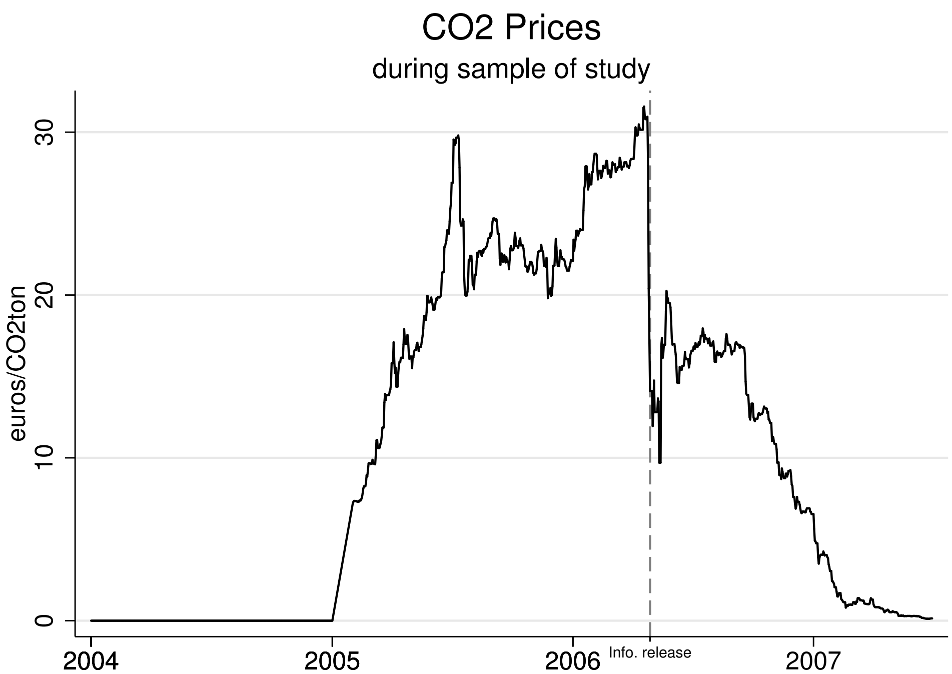
The day-ahead market trades 24 hourly electricity products that are cleared once a day. On the supply side, electricity producers, if not tied to a bilateral contract, submit supply functions

[10] 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%).

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

[12] Bushnell et al. (2013) and Zachmann and Hirschhausen (2008) explicitly exploit this change to analyze the response of firms to changing market conditions. We have decided not to exploit the discontinuity in the price to identify firms' responses due to coincidental regulatory changes in the Spanish electricity market around the break.

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



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 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

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.

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.

3.3 The Data

To perform the empirical analysis, we construct a data set that contains demand curves and the individual bidding curves submitted on a hourly basis by the Spanish electricity producers from January 2004 to June 2007.[13] 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).[14] Using similar techniques as Wolfram

[13] 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.

[14] 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

(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) and the short-run variable cost of operating and maintaining the plant (O&M).[15]

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 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 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 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. 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.[16]

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.

units (mainly CCGTs). This data are also used in Fabra and Toro (2005).

[15]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.

[16]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 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.

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.

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. Given that there is substantial variation in CO_2 prices, we can identify the pass-through from observed electricity price responses.

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.[17]

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 emission 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, market power and cost heterogeneity.

4.1 Price pass-through

To identify the effect of changes in CO_2 prices on electricity prices, we follow the conventional approach of estimating the pass-through rate by regressing the hourly wholesale electricity equilibrium price on the daily emissions price. The pass-through is an equilibrium outcome, and therefore we use controls from both the demand and the supply side to identify the equilibrium effect of the emissions price on the market price.[18] The main identifying assumption 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.

Our baseline regression is as follows:

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

[17] As explained in Section 3, 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%.

[18] Similar equilibrium regressions have been used in the pass-through literature (Besanko et al., 2005) or in the context of measuring the effects of gasoline prices on car prices (Busse et al., 2013).

where

$$
\begin{aligned}
p_{th} &= \text{hourly electricity equilibrium price,} \\
\tau_t &= \text{daily cost of the CO}_2 \text{ allowances,} \\
X_{th} &= \text{common controls,} \\
X_{th}^S &= \text{supply-side exogenous shifters and controls,} \\
X_{th}^D &= \text{demand-side exogenous shifters and controls,} \\
\omega_{th} &= \text{time fixed-effects (hour, day of week, month and year).}
\end{aligned}
$$

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 fossil-fuel prices (coal, gas and oil), as well as their quadratic terms and quadratic terms of their differences. On the demand side, we include economic activity indicatorsand weather, allowing temperature and wind to have a different effect on price depending on the month in some specifications.[19] On the supply side, we also include controls for renewable output, which is 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. Under specification (1), which includes the basic set of controls, the price pass-through is close to 1.11.

It is difficult to fully control for all changes in demand and supply that evolve over time and that could potentially be correlated with the evolution of the CO_2 prices, so specification (1) might have omitted variables bias. To mitigate 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 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

An alternative model to the price pass-through regression is one in which we consider the effect of the CO_2 price on market prices through its effects on the emissions costs of the marginal unit, i.e., we account for the emissions rate of the price-setting unit.

The baseline regression to identify the cost pass-through is very similar to the price pass-through

[19] This can be important, as a relatively warm day in the winter tends to reduce electricity consumption, whereas it will increase it in the summer.

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

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

	(1)	(2)	(3)	(4)	(5)	(6)
τ_t (ρ)	1.106	0.574	0.417	0.474	0.443	0.443
	(0.028)	(0.057)	(0.099)	(0.100)	(0.101)	(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.

regression, but we now use the marginal emissions cost instead of the emissions price only:

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

where ρ^c is our parameter of interest as it identifies the equilibrium cost pass-through and e_{th} represents the emissions rate of the unit that sets the price at a given hour, i.e., the hourly marginal emissions rate. 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_{th}. 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.[20] Finally, there are a few observations for 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 attribute the average emissions rate of 0.92 when coal is at the margin and an emissions rate of 0.41 when CCGT is at the margin, based on the distribution of actual emissions rates in hours in which they are observed.[21]

[20] In particular, we use observations that fall within 50 cents €/MWh above or below the market price. We have experimented with 25 cents, 1€ and 2.5€, and the overall results do not change significantly.

[21] Given that the Market Operator does not necessarily classify all hours as Coal or CCGT only, there still remain

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

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

	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
$\tau_t e_{th}$ (ρ^c)	1.614 (0.048)	0.932 (0.092)	0.731 (0.162)	0.763 (0.161)	0.775 (0.166)	0.795 (0.154)
Obs.	28,136	28,136	17,309	17,309	17,309	17,309
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, 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). The marginal emissions cost is instrumented with the emissions price. Robust standard errors in parentheses.

The hourly marginal emissions rate is likely to be endogenous, as the identity of the marginal unit is potentially affected by unobserved cost and demand shocks. In fact, when we regress the market price on the marginal emissions cost, the cost pass-through rate is negative, ranging from -0.17 to -0.22. The 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.

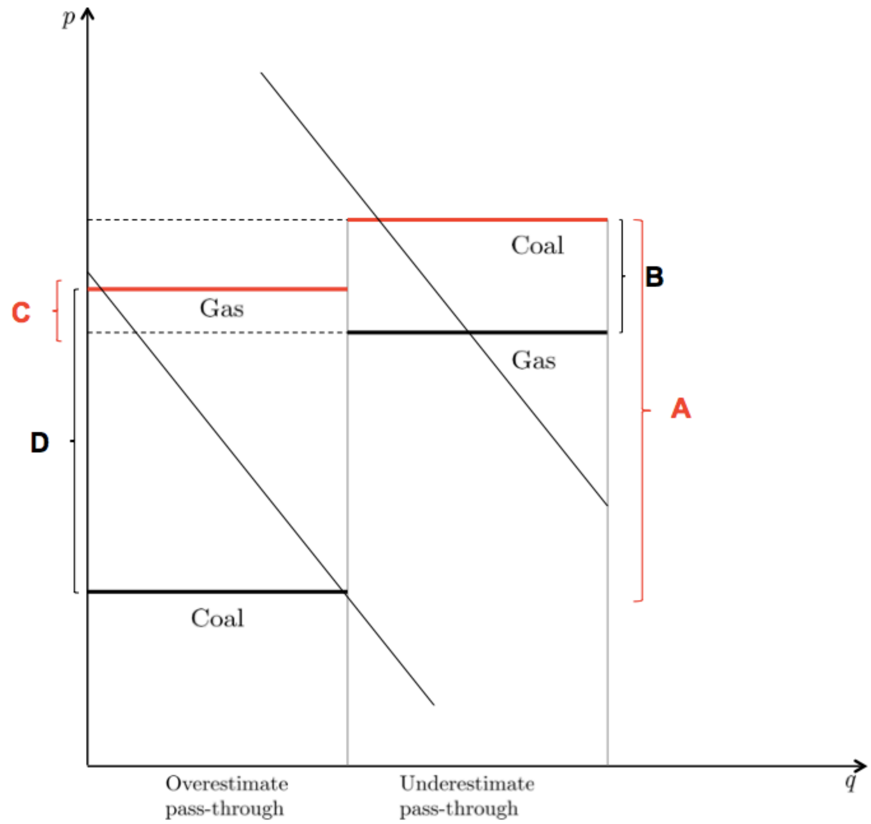
In order to get an estimate of the cost pass-through, we instrument the marginal emissions cost, $\tau_t e_{th}$ with the emissions price itself. The idea behind considering the emissions price as an excluded variable is that we are examining the effect of the emissions price on the market price *through* its effect on the emissions costs.[22]

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. When we control for month of the sample in specifications (2)-(6), we find that the cost pass-through rate is between 73-93%.

10% of the hours in which the marginal emissions rate is not observed. To complete all observations, we have experimented constructing the marginal technology by interpolating the marginal technologies reported by the Market Operator. For example, if coal is marginal at 2am and 4am, and pumped storage is reported marginal at 3am, we consider that coal is at the margin also at 3am. Results are similar if we include these observations instead.

[22]Note that this is not equivalent to substituting the endogenous emissions rate with the average emissions rate in the sample. By instrumenting the emissions costs, we include all other covariates in the first stage of the regression. For example, our instrumented emissions costs will present within-day variation through the hourly fixed effects, capturing the fact that emissions costs tend to be higher at night when coal is at the margin.

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



To try to disentangle 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. We allow the coefficients on input prices (coal, gas, oil) to change depending on which technology is at the margin.[23]

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 price interacted with a marginal technology dummy.

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.[24] 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 substituting 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

[23]In the appendix, we provide an additional specification that allows all coefficients to be different by technology group, which provides similar results to those reported here.

[24]This would not be corrected even if we split the sample in two. One situation in which a split sample would correct the selection is a case in which the hours in which coal or gas set the price were exogenously predetermined.

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

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

	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
$e_{th}\tau_t$ ($\rho^{c,Coal}$)	1.131	0.584	0.599	0.597	0.597	0.594
	(0.115)	(0.196)	(0.426)	(0.418)	(0.421)	(0.386)
$e_{th}\tau_t$ ($\rho^{c,CCGT}$)	2.045	1.020	0.787	0.872	0.911	0.996
	(0.064)	(0.124)	(0.261)	(0.255)	(0.258)	(0.235)
Obs.	28,136	28,136	17,309	17,309	17,309	17,309
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, 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). Input controls (oil, coal, gas) are allowed to depend by technology group. A technology dummy is included. The marginal emissions cost is instrumented with the emissions price interacted with the technology group dummy. Robust standard errors in parentheses.

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 60% and 100% respectively, which lay below and above the estimated 80% 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 important limitations. As we have discussed, it is difficult to obtain a clean identification with time-series variation only, as 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.). Even with month of sample fixed effects, estimates might suffer from omitted variables bias. Furthermore, this approach does not allow us to disentangle all the channels that generate the estimated pass-through. To explore these channels more closely, we turn into a structural model that takes advantage of detailed panel bidding data at the unit level.

5 Structural Decomposition of the Pass-Through

The reduced-form estimates suggest that there was an incomplete pass-through of emissions costs in this market. In this section, we rely on a structural bidding model to decompose the different channels that explain an incomplete passthrough. We proceed in two steps.

First, we use the model to identify how firms treat the costs of the emissions when bidding in the market. This is a necessary first step for quantifying the pass-through rate, as if the opportunity cost of permits were 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 pass-through estimates.

5.1 Bidding model

Consider a model in which market demand is given by $D(p;\varepsilon)$. Let $S_{-i}\left(p;u_{-i}\right)$ 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 emissions costs, $\tau e_i Q_i^S$, where τ is the permit price and e_i is firm i's emissions rate.[25] 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.

We can write firm i's profits in the day-ahead market as follows:[26]

$$\pi_i(p;\varepsilon,u) = p\left(D_i^R(p;\varepsilon,u_{-i}) - Q_i^D\right) - C(Q_i^S;u_i) - \tau e_i Q_i^S. \tag{5.1}$$

[25] 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}.

[26] We have omitted revenues from 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. Solving the FOC for p,

$$p = c_i + \tau e_i + \left|\frac{\partial D_i^R}{\partial p}\right|^{-1} Q_i, \tag{5.2}$$

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.

5.2 Estimating the bidding model

Based on the optimal bidding condition (5.2), we estimate the following empirical equation in those hours in which firm i is setting the market price through its marginal unit j:

$$b_{ijth} = \alpha_{ij} + \beta_i c_{jt} + \gamma_i \tau_t e_{ij} + \theta_i \left|\frac{\partial \widehat{D^R}_{ijth}}{\partial p_{th}}\right|^{-1} Q_{ijth} + \epsilon_{ijth}, \tag{5.3}$$

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,
$\frac{\partial \widehat{D^R}_{ijth}}{\partial p_{th}}$	=	estimated slope of residual demand curve,
Q_{ijth}	=	inframarginal quantity for firm i when unit j is at the margin,
ϵ_{ijth}	=	error term (cost shock, modeling error and/or firm optimization error).

The main parameters to be estimated are $\Theta = \{\beta_i, \gamma_i, \theta_i\}$. The focus of our interest is testing $\gamma_i = 1$, which would imply that firms, on average, consider that the emissions price reflects the opportunity costs of the permits. One important difference from the reduced form analysis is that this structural regression is based on the supply-side only. Therefore, demand shifters are excluded from this regression. The main identifying assumption behind the parameter γ_i is that the emissions price is exogenous to the Spanish electricity generators after controlling for other related supply shifters, which are captured in the model by the marginal costs of production.

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. 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

Table 5.1: Test based on structural equations

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

	All	**Firm 1**	**Firm 2**	**Firm 3**	**Firm 4**
(1) No FE	0.982	1.015	0.948	1.063	0.899
	(0.039)	(0.021)	(0.046)	(0.020)	(0.058)
(2) Unit FE	0.940	1.042	0.762	1.011	0.872
	(0.027)	(0.025)	(0.040)	(0.027)	(0.059)
(3) Unit FE + season	0.909	1.038	0.734	0.954	0.850
	(0.024)	(0.030)	(0.043)	(0.023)	(0.055)
(4) Spec.3 + RD excluded	0.931	0.999	0.979	0.932	0.744
	(0.027)	(0.019)	(0.035)	(0.034)	(0.060)
(5) Spec.4 + Markup (IV)	0.914	1.027	0.986	0.791	0.864
	(0.032)	(0.018)	(0.039)	(0.065)	(0.061)
Obs.	3,565,030	909,953	1,215,403	1,057,281	382,393

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

the extent that other costs might not be accurately reflected into this variable, we also introduce unit fixed effects.[27]

Finally, we need to make a modeling choice when estimating the structural equation, as the first-order condition is only valid for those units that set the price with positive probability (de Frutos and Fabra, 2012). In our baseline estimation, we use a weighted regression that weights those observations that are closer to the marginal price.[28]

Table 5.1 presents the structural estimates of the opportunity costs parameter. The estimation is 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. Whereas most specifications constrain the markup parameter to be equal to one ($\theta_i = 1$), in the fifth specification we allow the markup coefficient to be different than one. 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,

[27]Results are also robust to allowing the marginal cost coefficient to be unit-specific or to imposing the marginal cost coefficient to be equal to one, as suggested by the bidding model.

[28]We use a Normal kernel weight with a bandwidth of 3€/MWh as in Reguant (2012). As a robustness check, we include several specifications using different bandwidths and selection rules in the appendix.

except for specifications (2) and (3), and for firm 3. It has been documented that firm 2 followed an anomalous bidding behavior under Royal Decree 3/2006, thus suggesting that the estimates might be biased when we include this period in the sample.[29] The parameter estimated for firm 4, which is the smallest firm in the market, is also 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 firm 4 has very few gas plants, leading to less variation in marginal costs and emissions rates, making the identification more challenging.

Table A.2 in the appendix presents alternative specifications to the ones presented in this section, considering alternative kernel weights for the regression. The results are robust to using alternative weights as well as to using only the bids that exactly set the price, overall providing evidence consistent with the hypothesis that firms perceived the CO_2 price as the relevant opportunity cost of emissions.

Finally, as a robustness check, we extend the analysis of Reguant and Ellerman (2008).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. We extend the original analysis, focused on coal plants, to include all thermal technologies affected by the EU ETS. 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 emission 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,

$$b_{ijth} = \alpha_{ij} + \beta_{ij} c_{ijt} + \tau_t e_{ij} + \left| \frac{\partial \widehat{D^R}_{ith}}{\partial p_{th}} \right|^{-1} Q_{ith} + \epsilon_{ijth}, \tag{5.4}$$

where, given the previous evidence, we have assumed that the permit price reflects the true opportunity costs of emissions, i.e. $\gamma_i = 1$, and we have set the markup parameter equal to one, i.e. $\theta_i = 1$.

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. As shown in equation (5.4), 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.

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

We need to make a few assumptions to compute the new market price. First, 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 thus, the structural equation still reflects the marginal incentives faced by the firm. Second, given that the change in emissions costs is small, we take participation decisions as given.[30] Finally, 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, 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.[31]

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 through the effect of CO_2 on marginal costs.[32] 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 demand to be elastic by incorporating the actual demand curve in the market.[33]

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 infra-marginal 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.

Computing the new equilibrium with new markups in a supply function equilibrium can be challenging. We follow the approach of looking only at best response deviations, and examine ex-post whether the implied markup changes would be substantial.[34] 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 initial changes in markups that could 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

[30] 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.

[31] Admittedly, this is an ad-hoc way to capture the change in opportunity costs of hydro bids, motivated by the fact that the alternative option is to use the technology at the margin. 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).

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

[33] Note that this demand curve will tend to be more inelastic than the long-run electricity demand, so this estimate provides an upper bound on pass-through.

[34] Wolak (2007) follows a similar approach by looking at best responses, 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

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.

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, as shown in Figure 4.1.

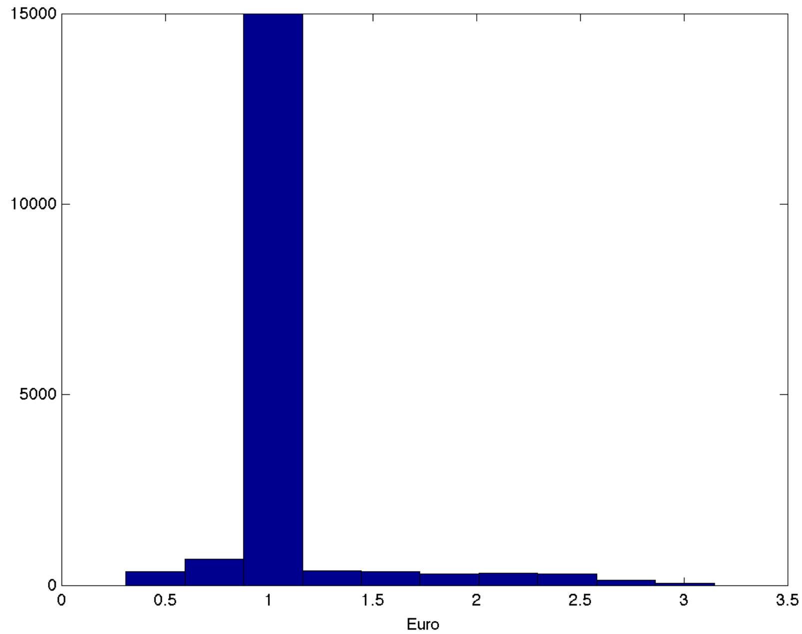
The role of technology switching and market power Given relative prices for coal and gas during the sample period, and the relatively low CO_2 prices during part of the sample, one would expect to observe little technology switching in a competitive setting. Hence, there remains the question of whether 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 could reflect production inefficiencies due to market power.

To explore this claim, we perform the same pass-through rate calculation as in counterfactual I, i.e., with inelastic demand and increase in bids proportional to the emissions rate of each plant. However, instead of using observed bids as a baseline, 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.[35] In contrast, technology switches occur in 19.06% of the hours using observed bids. These results suggest that there is more technology switching in the presence of strategic bidding behavior, as coal and gas are more mixed in the observed data than in the competitive supply curve. An alternative explanation is that our engineering cost measure masks some of the actual cost heterogeneity across plants that could generate changes in the merit order.

[35] 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 relative differences, although the percent levels 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.

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.

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 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 (counterfactuals III and IV). 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.

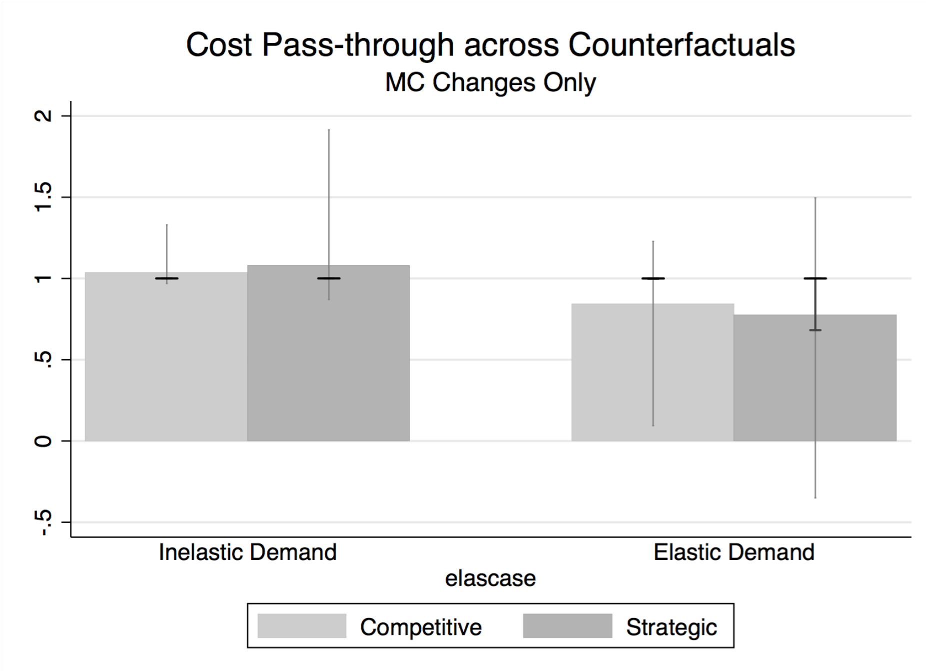
Combining the reduced form evidence with the structural approach, we find intermediate levels of price pass-through (around $40-60\%$) and levels of cost pass-through close to 80%. The simulated results suggest this attenuated cost pass-though is due to both demand response and market power. Also, both 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 emission 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 richness of the micro-level data has allowed us to perform structural estimations without imposing 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. This is particularly true for the larger firms with a diversified portfolio of different technology units. 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

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.

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.

From a policy perspective, the finding that firms fully internalized the costs of permits suggests that auctioning permits should have no inflationary effect on electricity prices. Several auctions have recently taken place in the European Union, but it is still too early to empirically check whether the degree of cost internalization indeed remains unchanged. Finally, the extent of pass-through reported here demonstrates that electricity producers benefited from windfall profits due to both free permit allocation and increased market prices.

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A Additional Tables

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

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

				Coal subsample		CCGT subsample	
	(0)	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
$e_{th}\tau_t$ ($\rho^{c,Coal}$)	-0.090	0.613	0.594	0.715	0.535		
	(0.071)	(0.188)	(0.386)	(0.092)	(0.138)		
$e_{th}\tau_t$ ($\rho^{c,CCGT}$)	0.669	1.091	0.996			1.221	1.029
	(0.036)	(0.119)	(0.235)			(0.147)	(0.293)
Obs.	28,136	28,136	17,309	14,677	10,324	13,459	6,985
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, 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). 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

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

	All	**Firm 1**	**Firm 2**	**Firm 3**	**Firm 4**
Ex-post Marginal	0.979	0.934	1.018	1.053	0.851
	(0.030)	(0.028)	(0.043)	(0.043)	(0.101)
Obs.	10,862	3,484	2,473	3,258	1,636
bw=1€	0.955	0.981	0.966	0.989	0.805
	(0.023)	(0.023)	(0.029)	(0.028)	(0.070)
Obs.	1,930,175	475,318	508,233	579,641	227,623
bw=2€	0.950	0.976	0.959	0.995	0.783
	(0.025)	(0.020)	(0.027)	(0.029)	(0.068)
Obs.	2,656,033	714,699	692,069	687,914	255,182
bw=4€	0.945	0.988	0.955	1.005	0.727
	(0.031)	(0.016)	(0.027)	(0.033)	(0.066)
Obs.	3,266,105	752,783	729,836	705,694	260,364
bw=5€	0.940	0.992	0.952	1.003	0.701
	(0.034)	(0.016)	(0.027)	(0.034)	(0.067)
Obs.	3,291,455	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. Standard errors clustered at the unit level.

Table A.3: Test based on operational patterns

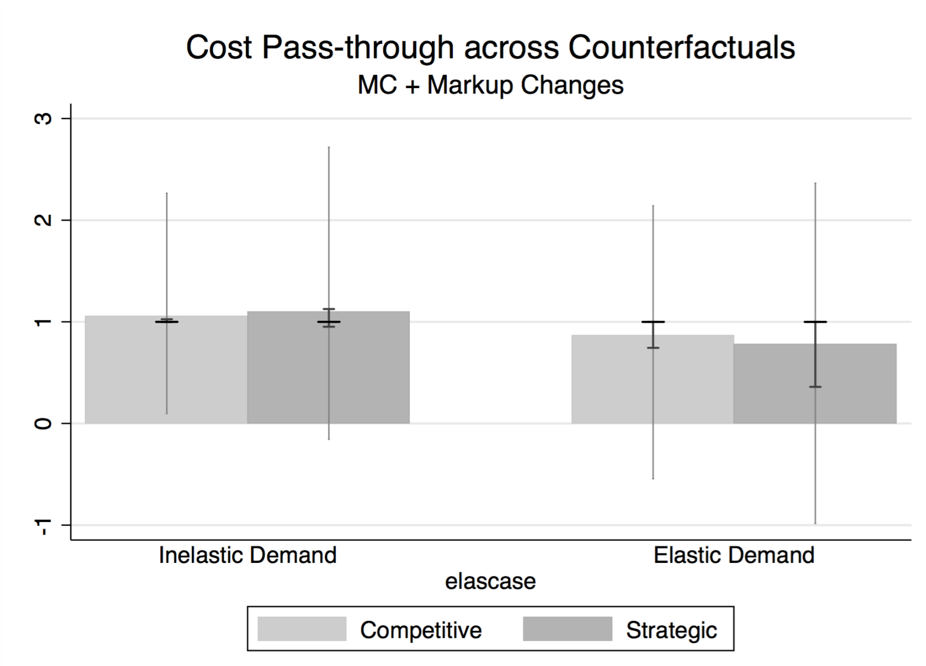
$$on_{jt} = \alpha_j + \beta_1 p_{jt} + \beta_2 c_{jt} + \gamma \tau_t e_j + X_{jt}\beta_3 + \omega_t \delta + \epsilon_{jt},$$

	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
p_t [β_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)
$e_i\tau_t$ [γ]	-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)
$-\gamma/\beta_1$	0.776	0.787	1.060	1.047	0.879	0.975	0.782
F-test (γ=β_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 €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). 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.

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.