Dottorato in Economia
XXIX CICLO

Tesi di dottorato

Electricity Markets and Environmental Policies: Evidence on the Electricity Price Pass-through in Italy

Dottorando: Francesca Mazzarella

Relatore: Prof.ssa Valeria Costantini

Coordinatore: Prof. Luca Salvatici

Electricity Markets and Environmental Policies: Evidence on the Electricity Price Pass-through in Italy

Francesca Mazzarella*

October 1, 2017

Abstract

This thesis empirically studies the complex interactions between environmental policies and the electricity price by analyzing the evolution of the electricity price pass-through of the European carbon emissions allowances (EU ETS). By exploiting plant level bid data for the Italian day-ahead electricity market for the years between 2005 and 2015 together with data on plant level emissions' intensity, the pass-through rate is estimated, using an instrumental variable strategy, separately for each one of the three phases of the ETS: between 2005 and 2007 (phase I), between 2008 and 2012 (phase II) and between 2013 and 2015 (phase III). The main result that this thesis uncovers a substantial decrease across the three phases of estimated pass-through that passes from being 70 percent in phase I to 30 percent in phase II and, finally, essentially zero in phase III. This finding is confirmed by the outcomes of an extensive set of robustness checks involving the performance of the instrument, the model specification and the analysis sample. The second main results concerns an assessment of the potential drivers of the pass-through decline. By exploring both supply and demand factors, the study reveals that demand factors can contribute to the observed reduction between phase I and phase II, but that the decline in phase III is best accounted for by changes in the supply side. In particular, the composition of the sellers in terms of a shift from traditional electricity generators towards financial operators triggered by regulatory reforms occurred in 2012 turns out to be a critical driver of the decreased pass-through. This results underscores the importance of accounting for the sophisticated trading strategies of financial traders in the design of policies affecting markets like the electricity and ETS markets where both these players and the traditional electricity suppliers are simultaneously present.

JEL: E32, Q58, Q54 Keywords: electricity, carbon emissions, environment, pass-through, financial traders

*Department of Economics, Roma Tre University. Email: *francesca.mazzarella@gmail.com*. I am grateful for the advices received from my thesis supervisor Valeria Costantini. I am also grateful for the comments received from Francesco Decarolis, Maria Gaeta, Chiara Martini, Andrea Pozzi, Luca Salvatici, Giancarlo Spagnolo, Francesco Sperandini and from the participants at the seminars at Roma Tre University and Stanford University where preliminary versions of this paper were presented.

Contents

I Introduction

Jointly addressing the goals of environmental protection and economic growth is a major societal challenge. In Europe, goals have been set to ensure environmental protection through the promotion of renewables, the enactment of energy efficiency standards and the reduction of CO2 emissions. The latter objective has been addressed especially trough the introduction of a cap-and-trade scheme know as European Trading Scheme (ETS).[1] The ETS as well as the other *green policies* interact in complex ways with energy markets affecting electricity, gas and gasoline prices for both residential and business users.

This clearly implies the need for a careful assessment of how energy markets respond to changes in the environmental regulations in order to properly trade-off the cost and benefits of various interventions. The pass-through of the ETS on electricity prices, that is the degree to which a change in the price of CO2 emission allowances is passed on to wholesale electricity prices, is thus a fundamental parameter whose knowledge is essential to evaluate both past and perspective policy reforms. It is therefore not surprising that a broad literature focused on estimating this parameter has developed. Nevertheless, the difficulties in reliably identifying this unobservable parameter in the face of data limitations and the lack of experimental variation, implies that much remains to be learned.

This paper contributes to a recent strand in the literature that seeks to overcome some of the identification problems through the use of detailed, plant-level data on electricity costs and emissions intensity.[2] In particular, I empirically estimate the impact of the ETS on the electricity price in Italy between 2005 and 2015 using plant-level data and find that: (i) the degree of pass-through is below the value of one that should characterize a competitive market, (ii) that this values steadily declines over time across the various phases of the ETS and (iii) that a change in the composition of suppliers, namely the marked increase in price-setting bids placed by financial traders that followed their expanded role after a regulatory reform of 2012, is a key driver of this pass-through

[1] In this study, I use the acronyms ETS to refer to the trading system and EUA to indicate the units defining the right to emit one tonne of CO2.

[2] See, among others, Fabra and Reguant (2014), who study phase I (2005-2007) of the ETS pass-through on the Spanish electricity price and Hinterman (2014), who studies phase II (2008-2012) of the ETS pass-through on the German electricity price. See Section 2 for a detailed review of the literature.

reduction.

More in details, the Emissions Trading Scheme was adopted in January 2005 by the European Union in order to curb CO2 emissions. In essence, under the ETS the EU governments set a cap on the amount of emissions, installations covered by the scheme receive tradable allowances to emit CO2 and, at the end of every period, they give back the amount of allowances required to cover their verified emissions. A company that has received an allowance can either use it to cover its emissions or sell the allowance on the market (to other companies that need additional allowances). In any case, emission allowances are an opportunity cost for companies and, therefore, producers should add the full costs of CO2 emission allowances to their other variable costs when making their decisions. This is the case even if the allowances are granted free of charge.

The ETS covers almost the entire power generation sector since in Europe most of the electricity is produced from CO2 intensive sources (like coal and gas). Hence, the ETS is likely to have a significant impact on electricity price. Indeed, several recent studies indicate that the ETS is an important determinant of electricity price.[3] Although the European Trading Scheme exists since 2005 and its effects on the electricity market have been extensively debated, a consensus on the quantitative implications of the CO2 allowances price on the electricity price is still missing.

This study contributes to the ongoing debate by implementing on the Italian data an analysis an instrumental variable approach that, in the spirit of the work of Fabra and Reguant (2014), exploits the availability of micro-level data consisting of the hourly bids of each individual plant selling electricity on the Italian Power Exchange. The bid data, combined with the characteristics of the plants in terms of their production technology and emissions intensity, allow me to formulate an estimate of the pass-through of emissions costs to electricity prices that is coherent with the microeconomic foundation underpinning the European Trading Scheme as well as other cap-and-trade schemes, namely that producers shall incorporate the emissions price as an extra element of their marginal cost for electricity production.

The main estimates indicate a pass-through ranging between 65 percent and 76 percent for the first phase of the ETS program. These values are clearly below the value of one that in this market would be expected under perfect competition. However, these estimates are also well above

[3]See Hinterman (2014), Fabra and Reguant (2014) and the other references discussed in Section 2.

what indicated by estimates based on more aggregate data using the country-wide average price, as often done in the existing literature, on micro-level bid data but without using instrumental variables to correct for bias in linear regression models. The estimates that I obtain for phase I are also similar, albeit somewhat smaller, to those obtained for Spain by Fabra and Reguant (2014) for the essentially the same period.[4]

Interestingly, however, when moving beyond phase I, the estimated pass-through declines substantially. I explore in detail this difference between the three phases of the ETS program and provide various pieces of evidence supporting the finding that indeed the pass-through halves in passing from phase I of the program (2005-2007) to phase (2008-2012), passing from about 70 percent to about 30 percent. Furthermore, and even more strikingly, the pass-through becomes statistically indistinguishable from zero during the latter phase of the program (2013-2015).[5]

This marked differences across phases is, to the best of my knowledge, a result that had not been discussed in the literature yet. To substantiate the validity of this finding, I extensively explore its robustness relative to a number of factors belonging to three sets of analyses. First, I inspect the performance of my instrumental variable strategy and illustrate how the unusual result of a lack of any pass-through effect in phase III is linked to the performance of the reduced-form estimate of the electricity price on the price of emission allowances. Second, I evaluate to what extent changes in the model specification and, specifically, the inclusion of additional controls for various demand and supply factors might change the baseline result. I find, however, no noticeable difference relative to my baseline estimates. Third and last, I consider various sample splits involving different markets (based on either the time or the geographical area covered), but again I fail to uncover any relevant difference thus confirming the results in the baseline estimates.

The analysis concludes with an assessment of the sources of incomplete pass-through that can explain explain the differences over time. This part of the analysis focuses in particular on whether these differences are driven by changes in strategic markups, price rigidities or demand factors. Changes in the price elasticity of demand are found to be a potentially relevant source of

[4] A more detailed discussion of the comparison between my results and those of Fabra and Reguant (2014) is presented in Section 2.

[5] The third phase of the program extends to 2020, but the sample analyzed converse only the period until the end of 2015.

the pass-through drop between phase I and phase II, but not of the further drop in phase III. The main findings, instead, regard the prevalence of the supply side factors to explain the level of pass-through identified in the Italian context for phase III. In particular, novel evidence is provided on the growing presence of virtual operators (i.e., financial traders active on the exchange, but who do not have generating capacity). The association between the growth in the role of virtual operators and the decline in the pass-through is suggestive that, despite the potential liquidity benefits that these operators might bring to the market, their strategies on the exchange create frictions capable of decoupling the ETS price from that of electricity. This results underscores the importance of accounting for the sophisticated trading strategies of financial traders in the design of policies affecting markets like the electricity and ETS markets where both these players and the traditional electricity suppliers are simultaneously present.

II Literature

This paper contributes to various strands of the literature on energy and environmental economics as well as, more generally, to the literature on the cost pass-through. Starting from this latter contribution, the results in this paper expand and complement those in Fabra and Reguant (2014) regarding the cost pass-through of CO2 emission price on the Spanish electricity price during phase I.[6] Like Fabra and Reguant (2014) and the follow up study by Hinterman (2014), the key methodological feature of this study is to exploit the richness of micro-level bid data from the plants active in the electricity auctions, the Italian ones in my case, combining them with plant level information about costs. I first review the key features of this important study, and the analyze the differences with this paper. Fabra and Reguant (2014) explores the impact of emission cost shocks on the transaction price for electricity markets. Using both a reduced form instrumental variable approach, as well as a structural model, the paper finds substantial pass-through, on average 80 percent of the cost shock is passed on in the wholesale market. To account for the potential endogeneity of the marginal emissions rate in the cost pass-through the authors instrument it with emission prices.

This pass-through is substantial both in magnitude and in comparison to previous studies. The typical rationalization for incomplete pass-through includes markup adjustment, costs orthogonal to the cost shock, also known as non-traded costs, and price rigidity. By contrast the authors show that the large pass-through is incentivized by the highly inelastic demand and that the uniform price auction used in Spain (as well as in Italy) allows for low cost and frequent price adjustment.

The authors use a structural model of optimal bidding, given the market structure, and find that, in addition to the common channels of pass-through incompleteness, a mismatch between firms opportunity costs and the observed cost shocks, rationalizes the less then full pass-through. The structural model also illustrates that with inelastic demand, and high correlation between cost shocks among firms there is little value to adjusting markups, which results in prices co-moving with cost shocks. The authors conduct several tests to quantify the relevance of these channels

[6]Establishing what is the pass-through in an industry is of key relevance to a number of questions, not limited the pass-through of environmental policies to energy and electricity prices, but including tax incidence (Marion and Muehlegger 2011) and a broad range of competition policy aspects, like the welfare effects of price discrimination (Aguirre, Cowan, and Vickers 2010), merger assessment (Jaffe and Weyl 2013), or the quantification of cartel damages (Verboven and van Dijk 2009). Thus, the results in this paper contribute to the broad debate about the quantification of this key economic concept.

finding the data to be consistent with firms fully internalizing the permit prices in their bidding behavior.

The results are highly robust. Using detailed micro data the authors are able to control for other, non-emission costs, allowing them to isolate the impact of emission cost shock from other changes in cost unrelated to emissions.

This important and influential study has opened a research line based on the use of bid-level data (see, for instance, the study of Hinterman, 2017 discussed below). Relative to their seminal contribution, my analysis differs in several ways. First, a difference between our studies that turns out to be crucial is the difference in the sample periods analyzed. Indeed, while for phase I (2005-2007) of the ETS both our estimates indicate a relatively high pass-through that is well above 50 percent, when I extend the analysis to the subsequent phases of the ETS (which are not analyzed in their study), then the estimated pass-through declines substantially. Although, my estimates are lower than those of Fabra and Reguant (2014) even for phase I (70 percent in my case compared to 80 percent in theirs), the difference is particularly striking when looking at the subsequent phases, when I estimate a pass-through that is between zero and 30 percent. These latter values are far from those in Fabra and Reguant (2014), but close to the broader pass-through literature, the finding of an almost complete pass-through is the exception rather than the rule. Several studies have measured, for instance, the pass-through of exchange rates to the prices of imported goods, and robustly they found pass-through estimates lower than 50 percent or less. This is the case, for instance, for those works that have looked at whether exchange-rate fluctuations are passed through to the prices of imported goods. Goldberg and Hellerstein (2013) find that only 5 percent of an exchange rate change is transmitted to final prices. Relatedly, Nakamura and Zerom (2010) estimate a pass-through of 25 percent for the same pass-through in a specific industry (coffee).

From a methodological standpoint, estimating the pass-through presents a number of conceptual and practical problems, as recently argued in MacKay et al. (2014). Their study shows that, in general, consistent estimates of cost pass-through are not obtained from reduced-form regressions of price on cost. Indeed, my study will use an instrumental variable approach to deal with bias problems. Moreover, the combination of micro-level data on plant bids and costs allows me to minimize the sources of the bias that MacKay et al. (2014) argue might arises even under standard orthogonality conditions.

A second strand of the literature to which this paper contributes is that regarding the empirical assessment of the ETS system, especially with reference to the electricity market. In this respect, this study is built on several previous works that look at how fuel prices and carbon emission costs affect the dynamics of power prices. Studies on the issue, include those on the United Kingdom by Bunn and Fezzi (2007), on Finland by Honkatukia et al. (2006) and on Germany and the Netherlands by Sijm, J.P.M., S.J.A. Bakker, Y. Chen, H.W. Harmsen, W. Lise (2005) and by Sijm, J.P.M., Y. Chen, M. Donkelaar, J.S. Hers, M.J.J. Scheepers (2006). All these studies find the ETS to have a strong positive effect on the price of electricity. An analogous finding is also presented in Reinaud (2007) who links allowance prices to the electricity prices and electricity costs for single industries in several EU countries.

Moreover, my paper is also related to some studies that have tried to assess the efficacy of market mechanisms created to curb polluting emissions. These studies, following the seminal paper by Joskow et al. (1998) on the US market for SO2 emissions created in 1990, try to understand whether in Europe the observed reduction in emissions below the ETS cap is due to over-allocation of allowances or to active reduction in emissions (Ellerman and Buchner, 2006), and how the structure of the allocation of emission allowances (i.e., the National Allocation Plans) affected firms in their investment decisions (Neuoff, 2006).[7]

A more recent assessment of the ETS system has been offered by Beat Hintermann in two studies. Hintermann et al. (2014) reviews the literature on allowance price formation with a focus on the empirical evidence from analysis of phase II of the European Emission Trading System (EU ETS). By creating a market for trading emission allowances, emission trading can equalize the marginal abetment cost of pollution. Firms profit maximization entails the purchase of emission permits so long as the cost of purchasing allowances is less then the cost of reducing emissions. The efficient allowance price is the costs of reducing emissions just below the market cap on permits, however failure to account for factors such as imperfect information, transaction costs, market power, borrowing and uncertainty can lead to a poor match between the efficient price and

[7]Schmalensee et al. (1998) is also a classical reference regarding the issue of measuring the efficacy of this US program in reducing pollution.

the market clearing price. A corollary of optimal permit pricing is that when no further abetment is needed for within-phase compliance the price of permits should fall to zero, which was not empirically observed. This begs to question the validity of allowance prices as an indicator of the efficacy of emission trading. Such price changes can be rationalized by dynamic behavior, such as uncertainty over future demand, and this paper explores the literature analyzing allowance price dynamics.

In addition to price changes, price levels are important in assessing market efficacy. The literature on price levels in emission market is not well developed due in part to the lack of observable counterfactuals and in part to the impact of other policies such as feed in tariffs, quotas and the link to the Kyoto Protocols flexible mechanisms. Hinterman (2014) concludes that overall the market functions well, but balancing economic theory with political feasibility implies that the market will never be truly economically optimal.

Hintermann (2017), instead, explores the impact of free allocation of emission permits to dominant firms on market outcomes accounting for the interaction between input and output markets. Without accounting for the interaction between input and output markets, efficiency is obtained simply by providing the dominant firm with a full allocation of permits. However, as this paper shows, once accounting for the downstream effects in the output market, the efficiency breaks down. Specifically the permit price acts like a marginal cost in the output market, but the firms only need to pay for permits above their allocated amount. This, in turn, incentivizes a firm to inflate the permit price, for example by buying permits in excess of utilization, as the permit price is what drives prices in the output market, rather then the firm cost of purchasing permits. Essentially a dominant firm is incentivized to crowd out smaller firms by increasing the cost of production thereby reaping the benefits of increased market power in the output market. The reverse incentives exist when a firm has a small allocation of permits relative to their utilization: if a sufficiently large portion of their permits must be purchased then cost of permit purchase outweighs the benefit of downstream market power. Interestingly, even when the output market is highly competitive there is still profitable price manipulation through the permit market. In addition to theoretical motivation, the paper provides empirical evidence exploring the permit purchase and emission utilization of the top 10 largest firms during the phase I of the ETS: the dominant firms are net purchasers in the permit market and systematically purchase more permits then their utilization, even accounting for demand uncertainty or price speculation. This finding by Hinterman (2017) turns out to be likely very relevant for the Italian market as well: while I have no direct data on the individual trades on the ETS market(s), several pieces of indirect evidence that I illustrate below point to the likely presence of similar financial strategies taking place through combined positions in the ETS and electricity markets.

Another interesting feature of my study relative to the existing research is that, by covering a longer time horizon than most existing studies, I am able to analyze data from periods in which the ETS system was arranged rather differently. In particular, I observe both periods when the emissions are grandfathered in (phase I and II) and when they are auctioned off (phase III). Ellerman and Reguant (2008) is an early study on how the allocation system might affect the ETS functioning. This paper tests the Coase theorem of the independence of operation and allocation in the on coal plants in Spain. The European Emission Trading System induced heterogeneity in the initial allocation of allowances based on past emissions with a quadratic adjustment rewarding cleaner generating capacity. The non-linear adjustment generates plausibly exogenous variation in initial allocation, which the authors use to estimate the impact of initial allocation on operation. The key identifying assumption behind their usage the non-linear adjustment to instrument for allocation is that the production choices are only influenced by the non-linear adjustment rule through the effect on initial allocation. This assumption is justified by the essentially linear relationship between marginal cost of allowances and emission rates. In many similar markets the Coase theorem does not apply, especially when there are substantive transaction costs, but the authors show that in the context of coal plants in Spain, and after accounting for endogeneity of allocation as well as price effects, the data is consistent with independence of operation and allocation. They also point out how failing to account for endogeneity or for price effects would lead to finding a correlation between operation and allocation suggestive of a violation of the Coase theorem. My results will offer a picture consistent with this analysis in the sense that, despite the major differences in the pass-through once the ETS switched to an auction-based allocation system in phase III, I will be able to ascribe the changes in the pass-through not to the timing of the change in the ETS allocation rule, but to supply side factors playing in the electricity market.

A specific strand of the literature on the ETS is that looking at the presence of "market failures" in this market. Koch et. al (2014) analyze the remarkable drop in the price of emission allowances in the EU (EUAs) from the start of phase I of the ETS though the end of phase II and beginning of phase III. There are three factors commonly attributed to the price decline and Koch et. al. provides estimates of their magnitudes and ability to explain the observed price variation. Building on the marginal abatement cost theory, where the price of EUAs should reflect the opportunity cost of reducing emission output by one EUA of pollutants, the authors find that international credits are not robust predictors of EUA price dynamics. They show that growth in the production of renewable energy robustly contributes to EUA price dynamics but that this and other abatement-related contributors only explain 10 percent of the EUA price changes. By comparison economic activity explains 40 percent of the observed variation. Taken together these results suggest that the primary driver of the price drop is not driven by a link between the cost of avoiding pollution and the authors suggest that industry beliefs about the future value of EUAs, perhaps though a lack of credibility of the ETS to impose binding EUA quantity constraints, may be an important diver of EUA price dynamics. This finding is also consistent with what I will discuss next in terms of potentially sophisticated trading strategies taking place in the electricity and ETS market.

Furthermore, within the context of the studies addressing the market failures of the ETS, an important contribution is that addressing the interaction of the national and international taxation system with the ETS. As discussed below, a major practical problems in the functioning of the ETS, especially in Phase II, has been the alleged misuse of allowances trading to implement value added taxes (VAT) frauds. I return to this issue in the next section, but it is useful in to mention in this section that several papers have looked into the question of the ETS taxation, see Costantini et al. (2013) and DAmato, Valentini and Zoli (2017). This latter paper, for instance, explores how the taxation of allowances transactions can serve to partially correct the distortions due to market power in a context where a subset of the firms are price takers, while remaining one has market power. It finds that an ad hoc taxation, involving a mix of taxes for net allowances sellers and subsidies for net buyers can be welfare improving. In the former paper, instead, Costantini et al. (2013) do not consider the case of market power, but focus on identifying the impact of ETS taxation when no other taxes are taken into account in order to illustrate how such taxation would impact a benchmark, cost effective ETS.

Laing et al. (2014) summarizes papers estimating the impact of EUs ETS on intended targets, CO2 emission reduction and investment in low-carbon technologies, and side effects, changes price and profits. Their meta analysis indicates that EU ETS cut CO2 emissions by an average of 40-80 million tons per year but that there is little evidence of an impact on investment in low-carbon technologies. With regards to pricing they find cost-pass-through ranging from 20-100 percent in electricity compared to the less then 50 percent pass-through found in diesel and gasoline. They also find a few firms reaped substantial profits measured in billions of Euros. They also point out the difficulty in disentangling the impact of ETS from the concurrent economic crisis on EUA utilization and price path. This latter aspect will be explored in my analysis toward the end of this study, where I will explore changes in demand and supply factors.

Finally, the third strand of the literature to which this paper is related regards the economic analysis of the electricity auctions. In particular, to understand the differences in the pass-through that I estimate both over time and I will look at the presence of price rigidities as well as competition and demand conditions in this market. In this respect, a relevant reference is Reguant and Ito (2015). This paper explores the buying and selling of electricity in a sequential market. The authors provide a model of price setting where the firms price in the forward market affects their residual demand in the within day market. Firms face a tradeoff between sales in the forward market and sales in the within day market which creates incentives for either short selling or arbitrage depending on the firms market power. Imperfect competition and constrained arbitrage ability result in a price premium between the forward market and the within day market. Specifically a firm that is sufficiently large tends to sell less then its electricity production in the forward market, generating large markups and selling the remaining supply at lower prices in the within day market. By contrast smaller firms can profit by arbitrage, over selling in the forward market only to re-by in the within day market where the price is lower. Under full arbitrage the price differential would disappear but market constraints, such as positive production being required to participate in the market, result in a positive price differential.

The authors use micro data to calibrate the model primitives and show how the observed data fits well to the model. The estimates also illustrate the trade off between efficiency, specifically production by the low cost firms, and customer surplus. Counterfactual Cournot exercises show

how the sequential market structure reduces deadweight loss though the reduced market power, induced by the existence of the forward market, by more then 60 percent while also increasing consumer surplus, via reduced costs, by up to 10 percent. They also illustrate the importance of liquidity in reaping the benefits of sequential markets, in the extreme if the within-day market is highly liquid, then even with no arbitrage the allocation is very close to efficient, reducing deadweight loss by more then 90 percent.

Labandeira (2012) estimates a random effects model for panel data to estimate residential and industrial electricity demand in Spain. The model has forward-looking suppliers who forecast short-term future demand from high quality, but incomplete data on demand. His estimates imply electricity demand is inelastic with respect to price in the short term but that there is also heterogeneity in the response to price changes between residential and companies/large consumers. Specifically companies and large consumers do not react, in the short run, to price changes but households are not fully inelastic and do react in the short-run. He also finds heterogeneity in elasticity by per-capita income with more wealthy provinces being less sensitive to price changes then those with less wealth. Interestingly he finds that calibrating income elasticity and price elasticity of gas to different values has very little impact on estimated elasticity of demand for electricity. This study, together with the following one by Labandeira et. al. (2017), represent important contribution that underpin most of my concerns with the demand analysis illustrated below in the text.

Labandeira et. al. (2017) conducts a meta analysis of price elasticity of energy demand. The paper explores the recent literature on estimates of price elasticity of energy with a focus on the short and long term drivers of elasticity results, both for energy overall and separately for electricity, natural gas, gasoline, diesel and heating oil energy products. Their meta analysis finds a short run elasticity of demand for electricity of -.21. This is a value remarkably close to the one that I estimate for the case of Italy. Their long run elasticity, instead, is -0.69. These elasticities are smaller then those found by Espey and Espey (2004), but relative to this study they are based on a different and more recent time period. Their analysis also show that estimated elasticities have a tendency to decrease over time, suggestive of income effects and or energy-efficiency improvements. Perhaps most interestingly they show that, in aggregate in models that adjust for industrial energy demand, most of the variation in demand is explained by fluctuation in the business cycle and thus, conditional on GDP, there is very little impact of prices on demand. However they also find that models estimating residential and commercial demands have substantially greater, in magnitude, short-term elasticities as compared to aggregate or industrial demands.

Two recent studies by Ignacia Mercadal are also close to my work and have been fundamental to point the attention to the role of financial speculators in understanding recent evolutions in the electricity auctions. Mecadal (2016) looks at the impact of a policy that exogenously increased the presence of financial traders in wholesale electricity markets in the US Midwest. Similarly to the Italian case, in the environment that she studies, wholesale electricity is sold in sequential markets with a forward market where electricity commitments are bought and sold and a within-day market where electricity is bought and sold to equalize supply and demand. Production firms set their quantities in the forward market and tend to sell at a premium above the within-day market. By comparison financial traders do not produce but rather arbitrage between the two markets thereby reducing market power in the forward market. The focus of the paper is on the equilibrium behavior rationalizing production firm pricing. There are three conflicting theorys on firm behavior. Firms could be acting dynamically, selling below optimal markups to de-incentivize entry, acting statically, by best responding to current market conditions, or engaging in tacit collusion, by charging higher markups then consistent with static behavior with the tacit collusion maintained though repeated interaction.

This paper provides a structural test of these hypothesis based on the comparison of elasticitys of demand firms actually face with the elasticity implied by their bidding behavior. Specifically if firms systematically price below the Nash static optimal prices then there is evidence of entry deterrence. Alternatively if firms systematically price above the Nash static optimal prices, then there is evidence of dynamically sustained tacit collusion. Empirically the paper shows that firms bids are above the static Nash optimum, suggesting tacit collusion and that firms changed their bidding behavior in advance of the policy implementation by reducing pricing. This behavior is highly consistent with the reduced incentives to collude when the value of collusion falls in the future, as is the case when there are more financial firms arbitraging electricity between the two markets. As such the data is most consistent with tacit collusion and an erosion of collusive incentives in anticipation of the policy.

This paper also contributes methodologically. First, by computing optimal behavior rather than imposing optimality, it allows to disentangle static vs. dynamic behavior. Second, by using machine learning algorithms, it defines the relevant market over which competition occurs in a nodal market. This latter contribution is important since there is substantial variation in the cost of supplying electricity by nodes and ex-ante it is not obvious how to divide nodes into separate markets, whenever this information is not provided by the regulator (as in the Italian case). Simply treating the whole network as market does not allow for identification necessary to compute the structural model, and the heterogeneity in cost by node makes such market definition unrealistic. With regards to welfare, the effects of the policy are somewhat ambiguous. While consumers pay lower prices, producers loose the ability to price discriminate and production may shift to less efficient firms/generators.

Birge, Hortacsu and Mercadal (2016), instead, studies the role of financial firms on the efficiency and the market prices in wholesale electricity markets in the US Midwest. As discussed above, financial firms have been introduced into these sequential markets to hedge against risk and to arbitrage rents between the forward market, and the within day market. However despite prevalence of active financial firms there still exist noticeable premiums between the forward and within day market. This paper explores activity by financial firms rationalizing the lack of observed arbitrage. First, the ability of a firm to arbitrage is bounded by its access to capital and by the transaction costs to arbitrage. However, the much more troubling finding is that some firms persistently buy at high prices and sell at low prices. While initially counterintuitive such behavior is consistent with firms trading in other linked financial markets, taking a loss in the wholesale electricity market to make profits in related markets though spillover effects. This type of distortion appears likely compatible with the types of behaviors that I observe in my data and it is thus very interesting to note that something similar has been documented in the US market as well.

The paper identifies the impact of financial players though transaction cost policy changes and finds evidence supporting the nefarious behavior that resulted in a 7 million dollar settlement for alleged market manipulation between Louis Dreyfus Energy Services and the Federal Energy Regulation Commission. Specifically the buy-high sell-low strategies are more prevalent when there is more market power by financial firms and the price gap between forward and within day markets are not particularly sensitive to the exogenous shocks to the transaction cost of financial firms. Interestingly, it shall be pointed out that this same firm is active in the Italian market and is one of the main actors of the expansion of financial players documented below. This bolsters the elements inductive to think that it is possible that distortions similar to those documented for the financial traders active in the US electricity markets are also happening in the Italian market, possibly in even more sophisticated ways that exploit the simultaneous market power in electricity and ETS markets.

In addition to financial players, frictions in the electricity auctions might also be created by bidders' failures to fully optimize their strategies. Hortacsu et. al. (2017) explores bidding behavior in the electricity spot market in Texas. Similar to Mercadal (2016), the authors do not impose a Bertrand-Nash equilibrium. Rather than using observed bids and imposing equilibrium bidding behavior, they use observed bids, detailed cost data and bounded rationality to explain market outcomes. This is justified by reduced-from evidence suggesting that many firms bid sufficiently far above their marginal cost to rule out Bertrand-Nash competition. Specifically the authors use a Cognitive Hierarchy model to specify sophistication types and beliefs and embed this in a structural model of bidding behavior. By imposing that the lowest sophistication type submits a perfectly inelastic bid function, and using the Cognitive Hierarchy iterative solution methodology they arrive at a type-specific unique best response function witch generates a unique equilibrium. Their results show that small firms behavior is consistent with low sophistication while large firms bid closer to what would be predicted by a Bayesian Nash model. Their counterfactual simulations also illustrate increasing sophistication increases efficiency and that there are even potential efficiency gains from small firms merging with large firms when there are no cost synergies though the benefits of sophistication.

Another set of results to which this paper is clearly very close is that looking at how both the electricity and the emissions markets respond to the business cycle. This is crucial because to understand the findings in this paper, especially given the relatively long horizon of the data analyzed in this paper, 10 years, between 2005 and 2015, a period that includes the most recent financial crisis. Indeed, understanding to what extent procyclical carbon emissions are, is an important first step for crafting effective environmental policy over the business cycle. Khan et al. (2015) study how carbon emissions respond to business-cycle shocks. The authors report that in the US context, carbon dioxide emissions are highly correlated with cyclical fluctuations: they increase during booms and fall during busts. Using data for 1973-2012, they seek to distinguish how different sources of the cycle impact the dynamics of carbon emissions. Their main findings are that emissions fall after unanticipated investment shocks, but increase after an anticipated investment shock. They fall with either anticipated or unanticipated technology shocks. They hence conclude that the typical assumption in the literature that unanticipated technology shocks cause carbon emissions to move with the business cycle has little support in the data both at the aggregate and the state-level.

In Bell and Joseph (2015), the authors explore the relative contribution of European economic crisis versus the ETS on the reduction of greenhouse gasses from 2005 to 2012. A set of linear models predict CO2 emissions, specifically models that include an indicator for the crisis and models that include both an indicator for the crisis and an indicator for ETS. The magnitude of the estimated coefficients are consistent with greenhouse gasses being primarily explained by the economic crisis rather then the EU ETS. While not necessarily identified, as the implementation of EU ETS and the economic crisis are likely correlated and the models assume no time trend or differences between locations not captured by GDP or input/output prices, the estimated effect of the crisis is substantial compared to that of the EU ETS, with only around 12 or 13 percent of the reduction attributed to EU ETS.

Related work is also that analyzing the opposite question, that is whether energy taxes may impact households and firms. A first study in this area is that by Flues and Thomas (2015) which explores whether households are impacted heterogeneously across the income distribution in a regressive manner. This would be due to the differential share of income being spent on energy by household, in particular energy costs compose a smaller portion of a wealthy households budget as compared to the poor. As such, an energy tax is imposed on a larger share of poor households budget compared to that of a wealthy household. Flues and Tomas (2015) use household expenditure data from 21 OECD countries, along with micro simulation, to assess the distributional effects of energy taxes. By decomposing energy taxes burdens by source, specifically transport fuels, heating fuels and electricity, the authors show that both expenditure and income measures indicate that electricity taxes are regressive. They also show the heterogeneity of the tax impact on larger household, rurally located households and those with a head of household less then 60 years of age, all categories incurring a larger energy tax burden. However the authors appropriately emphasize that the 21 OECD countries were not randomly selected, in particular differences in relevant sociodemographic composition between omitted countries and those used in analysis suggest these estimates should not be assumed to be representative of the entire set of OECD countries.

Most elasticity and demand response estimates of energy markets either aggregate all energy products together or focus on one particular energy product, such as electricity or natural gas. By comparison, Labandeira et al. (2008) use a micro simulation model to estimate the impact of a 50-Euro tax on CO2 emissions that accounts for heterogeneity access and utilization of different energy sources in Spain. They point out the substantial variation in the availability of energy products by geographic features, such as natural gas being more prevalent in large cities and fossil fuels being more prevalent in smaller cities. The level of disaggregation employed in this study allows for a rich consumer demand that can capture differential elasticities throughout the income distribution. Instrumental variable estimates correct for measurement error in total expenditure and find substantially larger price elasticities for electricity then pervious literature. Specifically they find a -.78 energy demand elasticity. Their micro simulation results indicate a significant behavioral response by households to the 50-Euro tax. They find a large reduction in CO2 emissions with relatively minimal welfare losses and moderate distributional effects. They also find substitution between electricity and liquid petroleum gas (LPG) where a reduction in CO2 emissions from less electricity being partially offset by an increase in the use of LPG resulting in a net 17% reduction in total emissions. It is important to point out that their simulation model imposes the tax on consumers, or equivalently imposes a pass-through of 1, and thus with less then full pass-through the impact of the tax would likely be smaller in magnitude.

Regarding the impact on firms, Petrick and Wagner (2014) estimate the impact of EU ETS on German manufacturing firms. They use a difference in difference semi parametric approach, exploiting heterogeneity in ETS participation and the initiation of phase I of the program, to quantify the impact of ETS on firm level outcomes. They estimate a one fifth reduction between 2007 and 2010 in CO2 emissions between treated firms and matched control firms, but find that the reduction in CO2 emissions is achieved not by reduced electricity use but rather though improved energy efficiency and reduced gas/petroleum. Despite the adjustments in production practice there is no effect on employment, gross output or exports.

III Theoretical background

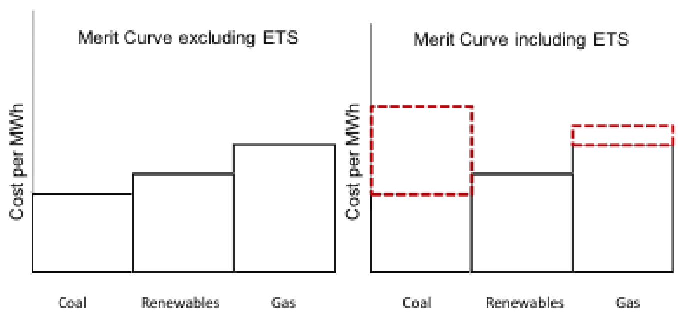
The interaction between the electricity price and the ETS is rather complex. In order to formulate a baseline theoretical framework to think about this interaction and its possible empirical implications, it is useful to separate the discussion in two parts. In the first, I seek to describe the most basic economic forces that are at play in an environment where firms are price takers in the market for allowances and were we abstract away from any potentially complex financial trading schemes involving the interaction between the electricity and the allowance prices. In this part, I focus on describing how, for an individual producer, the EUA price represents an opportunity cost, how this cost is passed-through to electricity price and why the form in which allowances are given out by governments (for free or at a cost) should not impact production decisions. In the second part of this section, instead, I will try to broaden the analysis in several directions: market power in the emissions market will be considered along with the possibility of financial trading schemes aimed at exploiting the linkages between the ETS and the electricity markets. In this respect, I will discuss the role played by purely financial operators that are gradually coming to play a major role in both these markets. In this second part, I will also specify the main elements that the empirical analysis will reveal and discuss how they can be all tight together in a single conceptual framework. These first two subsections that follow are thus important to describe the factors that are behind different levels of the pass-through. However, since the results from the empirical analysis will also emphasize a substantial decline over time in the pass-through rate, it is relevant to explicitly discuss how the elements described in the first two subsections can be part of the explanation of the pass-through dynamics observed in the data. In the third and last subsection, I thus address the question of what are the drivers of the changes in the pass-through.

III.1 Basic forces at play

At the most basic level, there are two key economic insights regarding which role the ETS plays on the electricity price: i) a positive price on CO2 emission allowances corresponds to an increase in a producer's marginal cost of generating electricity through a carbon-emitting technology and ii) an increase in the marginal cost of electricity generation is passed through to electricity price in a way that is proportional to the degree of competition in the market.

The first element can be graphically represented through the example in Figure 1. The supply schedule for the electricity market is typically modeled as a step function, the *merit order* curve. In a competitive market, the spot electricity price equals the variable cost of the marginal producing plant (the one with the highest marginal cost among the suppliers who meet demand). Peak prices also include the remuneration of capacity when new investments are needed. Figure 1 shows the effect of a positive CO2 emission allowance in a stylized model of the Italian merit curve, drawn only for the three most important generating sources and disregarding exact quantities.

Figure 1: Merit Order Function



The figure illustrates a stylized example of a *merit order* curve. I draw the curve considering only the three most important generating sources for Italy and disregarding exact quantities. On the left the EUA price is zero. The panel on the right considers a positive EUA price. The greater CO2 emissions' intensity of coal-based generators induces an higher price increase for these sources relative to both gas-based generators (for which the increase is small, but positive) and renewable-based generators (for which the increase is zero, under the assumptions that these generators are excluded from the set of operators under the ETS.).

The panel on the left is drawn without the ETS or, analogously, when the EUA price is zero. The panel on the right considers an EUA price of €20, as it approximately was in 2005/2006.[8] The rise in the marginal cost of each technology is proportional to its CO2 emission intensity. A standard combined cycle gas turbine produces about 0.66 tonnes of CO2 per MHw of electricity, while the analogous figure for coal generation plants is 1.05 tonnes of CO2 per MHw of electricity.

Thus, the increase on the coal plants production cost per MHw of electricity produced is larger

[8]This ignores the presence of value added taxes (VAT) on transactions involving CO2 allowances, which I discuss in the next section.

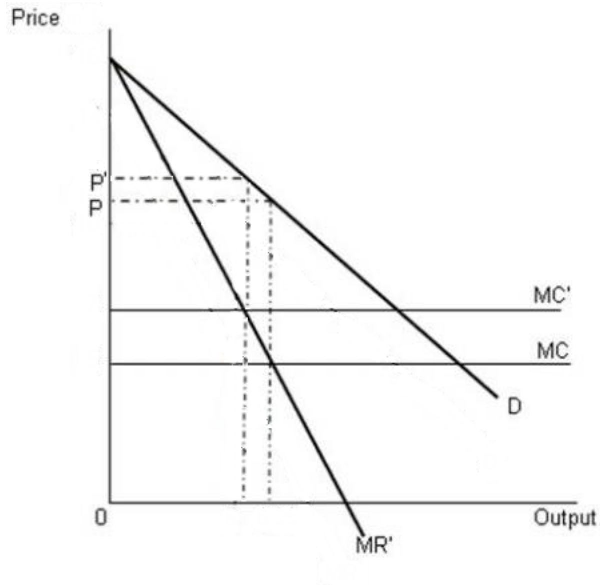
than that faced by gas plants. In this example, this differential increase is large enough to change the merit order, moving coal from being the least costly to being the most costly form of production. For a given demand schedule this upward shift of (part of) the supply schedule implies a higher equilibrium price. Therefore, given that in Italy most electricity generation occurs through three carbon emitting sources, namely gas, coal and oil, the price of allowances is expected to influence electricity prices.

In the short term, before any technological update is performed, the variable marginal cost of high-emitting technologies is thus raised and, as a consequence, some types of power generation become more expensive and less competitive than others. In addition to the short-term effects, in the long-term, the ETS may also affect both supply and demand. For supply, the additional cost of CO2 creates a disincentive to invest in high-emitting technologies, like coal, while it creates an incentive to invest in low or no-emitting technologies, like wind. On the demand side, in the long run adjustments are also possible as more power efficient appliances and machineries can be adopted to better adjust to higher prices.

The second key element involves how much of the increased marginal cost should producers pass-through. An emission allowance represents an opportunity cost. Under perfect competition, a company should add the full cost of CO2 emission allowances to its other marginal variable costs when making its bid, even if the allowances are granted free of charge and even if it receives enough allowances. In fact, a company that has received an allowance can either use it to cover its emissions resulting from its production, or sell the allowance on the allowances market to traders or to other companies that need additional allowances.

However, when a producer has market power, the degree of pass-through will differ relative to the case of perfect competition. Suppose, for instance, that we look at the problem of a producer in a monopolistic competition environment. A simple example with flat marginal production cost and linear demand, as that in Figure 2, can clearly illustrate how an increase in the marginal cost from MC to MC' leads to a smaller price increase, from P to P', so that: $(P'-P) < (MC'-MC)$. Since the optimizing behavior requires to set the price as the one ensuring that the marginal revenue equals the marginal cost, a parallel upward shift in the marginal cost curve leads to a less than proportional increase in the optimal price.

Figure 2: Pass-through in an Imperfectly Competitive Market



In the figure, I present an example of how market power is associated with an incomplete pass-through in the context of a linear supply and demand model. The figure illustrates how the equilibrium price increases from P to P' when the marginal cost increases from MC to MC'. The incomplete pass-through is evident by noticing that $(P' - P) < (MC' - MC)$.

The exact amount by which the pass-through differs from one depends on the characteristics of both the supply and the demand for electricity. In its most general form, the typical optimization condition in an oligopoly environment with operators possessing multiple production plants entails a relationship linking the optimal bid to both cost and strategic elements: $\boldsymbol{p}\text{=}\boldsymbol{mc} - (\Omega D_p \boldsymbol{q})^{-1}\boldsymbol{q}$. Where $\boldsymbol{p}$ is the vector of optimal electricity prices set by all producers submitting a separate bid for each one of their plants operating the market; $\boldsymbol{q}$ is the associated quantity offered and $\boldsymbol{mc}$ is the associated marginal cost (inclusive of the full opportunity cost of the EUA spot price); Ω is an ownership matrix, that relates together all plants belonging to the same producer; and, finally, D_p denotes the derivative of the demand function with respect to price. Thus, the electricity price results from both a mc term, that shall change as the EUA price changes, and a strategic markup term, that will also change, unless there is perfect competition in which case the markup is zero.

This stylized representation reveals the importance of the pass-through as a key element to assess the degree of competition in a market. Furthermore, a similar effect to what described above in terms of the optimization behavior of a monopolistically competitive multi-plant operator occurs when multiple operators collude to keep the electricity price high, as also in this case the pass-through will be less than one. However, if collusion is present the degree to which the pass-through is reduced relative to the case of full competition is not univocally pinned down, absent other information on the functioning of the cartel agreement. There are at least three factors that are likely important to asses the potential implication of collusion between suppliers. First, the illegal nature of collusion makes hard for cartels to adjust prices given the risks connected to explicit communications and to the impossibility of writing (and enforcing) contractual agreements. This feature has been found to empirically matter to explain the price rigidities observed in industries dominated by cartels where, indeed, the price variance tends to be lower than the input cost variance (see Abrantes-Metz and Bajari, 2012). Second, for the same reasons described above a cartel might find easier to coordinate on price increases in response to positive cost shocks than to coordinate on price decreases. This feature, asymmetric response to the direction of the cost shock has been extensively discussed in the literature (see, for instance, Peltzman, 2000, and Tappata, 2010). Third, the specific working of the cartel agreement might impact the degree of pass-through as, for instance, cartels able to coordinate through side payments (i.e., "strong cartels"') and larger cartels including all or nearly all the firms in the industry, might be associated with a degree of pass-through rather close to that an optimizing monopolist would induce. On the other hand, cartels operating without transfers (i.e., "weak cartels") or including a small fraction of the suppliers might be associated with a pass-through substantially different from that of a monopolist.

Finally, it is crucial to mention that while the above discussion has focused on the supply side, also the demand side plays a key role in the determination of the pass-through rate. As the case of linear demand and supply can easily illustrate, the elasticity of demand contributes to determine the rate of pass-through. Indeed, in the linear case the formula describing the price (P) change in response to a cost (C) change is: $dP/dC = -D_q/(D_q - S_q)$, with S_q and D_q being the inverse supply demand functions. Hence, the pass-through in this environment increases with the elasticity of supply, and decreases with the elasticity of demand. In the context of the electricity markets that studied here, the supply is typically considered rather elastic (net of technology-specific problems related to the start up cost of certain types of plants), while demand is typically considered almost perfectly inelastic, especially in the short term. Due to these features, and to the fact that the high market concentration in the Italian electricity generation sector is highly suggestive of the presence of market power, my discussion of the imperfect pass-through will tend to focus mostly on the role played by producers' market power. Nevertheless, a force that might be relevant and that I will later explore is represented by the gradual shift in demand over time from rigid demand by the "Single Buyer" (the entity buying for consumers in protected tariffs) to demand by individual firms and, even, households. To the extent that this represents the possibility of a less inelastic demand, it might also be a force driving some changes in the pass-through.

III.2 A nuanced view of the links between ETS and electricity markets

Compared to the baseline setting described above, the relationship observed in practice for the ETS and the electricity markets across Europe is certainly further complicated by the specific features of how the ETS is arranged and, in particular, by the fact that the same firms might have market power simultaneously in both the electricity and the ETS markets. As some of the studies referenced earlier have shown, this is certainly the case for at least one of the ETS characterizing features: the way the allowances are given to firms. The free allocation of phase I and II, have been partially replaced in phase III by an auction-based system used to sell about half of the allowances that are expected to be needed in phase III.

Theoretically there are conditions under which production choices are invariant to initial allocation. Because the permit price is driven by market forces, its price should be equal to the marginal abatement cost of reducing pollution. That is, for a given EUA market price, a firm that has received allowances for free has an opportunity cost of consuming emission permits by producing electricity that is equal to the cost that the same firm were to face in case, absent a free allocation of the permits, it would sustain to purchase them at market price.

Clearly, while the production choice is identical in the two situations of free and costly acquisition of allowances, the profits earned by the firm differ as they are lower in the situation of a costly acquisition. Even in this case, however, the situation can be very different depending on the degree of pass-through. With a pass-through close to one, it would be electricity purchasers who bear the extra cost of the allowances as the cost of allowances is passed to them in the form of higher electricity prices. Profits could thus, in principle, remain unaltered for the producers. By the same logic, with permits that are given for free and a high pass-trough, an higher EUA price translates into higher producers' profits.

Nevertheless, these considerations become more nuanced once the possibility of market power is allowed also in the permit market. In particular, as shown by Hintermann (2017), it will be not true anymore that it is irrelevant for production choices whether permits are given away for free to producers or at a cost. Thus, as argued below, not only the profit sharing between supply and demand changes, but also the actual production choices. Furthermore, as I will argue, even absent downstream market power the optimal permit trading is a function of initial allocation and this can result in the price of permits typically not reflecting the marginal abatement cost.

The next two subsections will extend the model of Hintermann (2017) to account for features that, as the following empirical analysis will show, appear to be amongst the most salient elements characterizing the dataset that I collected. The first feature that I discuss is the possibility of a positive price on emission permits despite the total supply of permits exceeding the total demand of emission. I will argue that, as shown by Hintermann (2017), this can be rationalized by demand uncertainty: firms choose to hold permits in excess of utilization to influence the price of electricity in the downstream market and to reduce competition by increasing the entry and operation cost of potential competitors, with no or less generous initial allocations. The second feature on which I focus is in part driven by the first feature. It consists of the decreased presence of production firms among electricity sellers. I argue that this is a strategic response to permit price inflation by large permit holders and that, at least in part, it is due to the unintended incentives to financial players generated by the link between electricity derivatives and permits prices. This section concludes with a discussion of why these features can be important to understand not just the level, but the changes in the pass-through over time.

A. Excess permit holdings and non-marginal abatement cost permit price

To understand the incentives that firms face, I will consider a variation on the model of Hintermann (2017). In particular, I will follow the model of Hintermann (2017) to illustrate how market power induces a link between the initial allocation of permits and the deviation from pricing permits at the marginal abatement cost. In the next section, I will then extend the model by adding an additional player, a financial trader, and show how the incentives and strategies of the financial player alter the equilibrium permit prices.

The environment consists of a dominant firm (or several colluding firms) and a price-taking fringe. For notational ease, label the dominant firm player 1 and fringe firms will be indexed by i $\in$ (2, . . . , N). The fringe firms have no market power and thus are price takers in both the output market, where electricity is sold at price p, and allowance market, where allowances are traded at price σ, and firm i has an initial allocation of emission permits equal to $\bar{x}_i$. The fringe firm i chooses output q_i, emissions e_i and permit holdings x_i to maximize profits subject to an emissions constraint:

$$\max_{q_i,e_i,x_i} \Pi_i = pq_i - C^i(q_i,e_i) - \sigma(x_i - \bar{x}_i) \quad \text{s.t. } e_i \leq x_i \tag{1}$$

Where $C^i(q,e)$ is the cost for firm i of generating q units of electricity and e units of emissions. Consider the dominant firm to be endowed with multiple types of energy producing generators, such as coal, oil and natural gas. A firm, in the short run, is constrained to use the generators it has and thus the firm must make a tradeoff between cost per unit of output and emissions per unit of output. Specifically, let cost be increasing in quantity, $C^i_q > 0$, and, as a firm will use its lowest cost generators first and then switch to the higher cost generators only after exhausting the capacity of is lower cost generators, the cost of production is convex in quantity for any given level of emissions, $C^i_{qq} > 0$. Similarly, for any given quantity, it is less costly to produce at higher emission levels, $C^i_e < 0$, and the cheapest to run generators also generate the most emissions per quantity, $C^i_{ee} < 0$.

Hintermann shows that the optimality conditions of this problem are independent of the amount of free allocation $\bar{x}_i$ and that firms equate price with marginal cost in both markets, $C^i_q = p$ and $-C^i_e = \sigma$. This means that the fringe firms' optimal output, emissions and permit decisions are a function of market prices, $q^*_i = q^*_i(p,\sigma)$ and $e^*_i = x^*_i = x^*_i(p,\sigma)$. Let Q^f be the quantity of electricity produced by the fringe firms, $Q^f = \sum_{i=2}^{N} q_i$.

By contrast permit purchase decisions by the dominant firm, denoted as firm 1, impact both the permit and the output price. Specifically the dominant firm can increase the permit price by purchasing permits or decrease the price of permits by selling permits, $\frac{\partial \sigma}{\partial x_1} > 0$. Since the permit price determines the optimal quantity produced by the fringe firms a change in the permit price induces a change in the quantity produced by the fringe firms, $\frac{\partial Q^f}{\partial \sigma} < 0$, and thus even if the dominant firm has no direct market power in the output market, p invariant to q_1, the dominant firm can alter the equilibrium price in the output market though its permit holdings:

$$\frac{\partial p}{\partial x_1} = \frac{\partial p}{\partial Q^f} \frac{\partial Q^f}{\partial \sigma} \frac{\partial \sigma}{\partial x_1} > 0; \;\; Q^f = \sum_{i=2}^{N} q_i \tag{2}$$

The dominant firm considers the fringe firm policy functions and the impact of permit purchase on both the output price and permit price when maximizing its own profits. Hintermann shows there exists an interior solution with an active dominant firm, $q_1, x_1, e_1 > 0$, and that the dominant firm's actions are characterized by a set of optimality conditions including:

$$\sigma + (x_1 - \bar{x}_1) \frac{\partial \sigma}{\partial x_1} = \frac{\partial p}{\partial x_1} q_1 - C_e^1 \tag{3}$$

This condition relates the effect of dominant firms permit holdings on the market prices in both the input and output markets, the left hand side reflects the change in the marginal cost of electricity from a change in permit holdings, taking into account the initial endowment, while the right hand side reflects the change in profits from the price effect in the downstream market. It then also follows that the optimal permit holdings are increasing in the initial allocation and explains why a firm would hold permits in excess of utilization, even with no uncertainty over demand.

B. Change in market composition

The second feature, the shift in the market from being primarily composed of production firms to being primarily composed of financial firms comes from the link between permit prices and financial derivatives tied to the price of electricity. The logic behind allowing non-production firms, i.e. financial players, to participate in the permit market comes from the intuitive link between the number of market participants and the degree of competition. The model in the previous section relies on the ability of the dominant firm to influence the market price of permits and thus the presence of an additional player with market power in the permit market could weakens the link between the dominant firms permit holdings and the price of permits, $|\frac{\partial \sigma}{\partial x_1}|$. However this reasoning assumes that financial players incentives are strictly profit making in the permit market. Just as production firms participate in both permit and output markets financial players can participate in both permit and derivative markets.

Derivatives are important financial tool for mitigating risk due to, for example, cyclicality driven by the business cycle. The majority of derivatives are bilateral agreements giving a electricity buyer (seller) the right to buy (sell) electricity at a predetermined price at a later date. For example, under a ‘two way hedge’ or ‘swap’, the seller agrees to pay the buyer (or receive from the buyer) the difference between the agreed contract price, the ‘strike price’, and an agreed future spot price if this is above or below the agreed contract price for any trades taking place before the derivative expires (Chester and Rosewarne, 2016).

Returning to the model above, let us consider a financial player, player $N+1$, as a participant with market power in the permit market and a price taker in the electricity derivative market. As illustrated above, permit purchase influences the output price in the electricity market and thus the purchase of permits has an indirect effect on the value of derivatives linked to the electricity market. As such a financial firm with holdings in derivatives that hedge against a fall in the price of electricity can, for instance, implement the following example trading strategy:

1. Buy permits at a high price and sell them at a low price, taking a loss in the permit market but also decreasing the market price of permits.

2. The decreased price of permits then leads to lower prices in the output market though market power effects.

3. The lower prices in the output market make the derivatives more valuable resulting in a profit in the derivatives market.

Note that the above example shows a profitable strategy for a financial firm holding derivatives that hedge agains price drops, however there is a symmetric strategy for firms holding derivates that hedge agains price increases. Specifically:

1. Buy permits, taking a loss in the permit market but also increasing the market price of permits.

2. The increased price of permits then leads to higher prices in the output market though market power effects.

3. The higher prices in the output market make the derivatives more valuable resulting in a profit in the derivatives market.

If there is only one financial firm, then the firm can do even better, over time, alternate between the two strategies. For example, the firm could initially start with a portfolio of derivatives hedging agains price rises and buy permits, engaging in the first strategy, which will increase the value of the firms derivatives while also decreasing the value of derivatives that hedge agains price falls. Then, the firm can sell its derivatives and buy a new portfolio of derivatives that hedge agains price falls. The firm next sells its pollution permits at below market price, engaging in the first strategy, causing a reversal in the value of the 'one-way-hedge' derivatives. In such a case the financial firm's alternating strategy will result in high variance in price of permits.

The above strategies are only meant to be examples of the potential strategies that traders with market power can implement. However, they clearly illustrate the point that, once the possibility of market power is allowed for, the types and complexity of strategies linking the ETS and electricity markets drastically grow and open the door to potential manipulations not dissimilar from those documented by some of the literature reviewed in Section 2. Therefore, the shift in composition of the players from electricity generators to financial traders might certainly be associated with differences in the observed levels of pass-through rate. I conclude this section by briefly summing up the four main motives that might be behind the observed evolutions in the pass-through rate.

III.3 What can drive changes in the pass-through?

In the empirical analysis, particular emphasis will be given not only to the level of the pass-through, but also to a novel result indicating a substantial decline in the pass-through rate in the Italian electricity market over the sample period analyzed. To more explicitly bridge the above discussion of the determinants of the level of pass-through to what can determine dynamics in the pass-through rate it is useful to separate and briefly discuss all the major potential drivers.

A. Changes in the suppliers market power

The discussion above makes clear that any exogenous change bolstering the suppliers' market power would also induce a decline in the pass-through rate. This is a mechanical result linked to the optimal choice of prices at different levels of market concentration. In practice, we could observe such change as a reduction of the number of suppliers or as a reduction of the dispersion in how much each of them sells (as, for instance, an increase in the HHI index would capture). Both of these measures will be observable in the data and I will control for them. Of crucial importance, but harder to observe, would be a shift toward a more collusive pricing behavior, for instance due to the enlargement of a cartel to include more players or the more stringent enforcement of a cartel agreement. Although direct evidence on cartel behavior in the electricity sector is not available, I will be able to rely on measures like the changes in the variance of bids and the potential asymmetry in upward/downward pass-through which, as discussed above, are useful proxies to capture potential cartel activities.

B. Changes in the pricing frictions

Although fully absent from the above discussion of the baseline, static model, in a world of dynamically changing costs the extent to which prices respond is necessarily also linked to any friction present in the price adjustment mechanism. The nature of the Italian electricity market, which is mostly based on a public exchange and not, for instance, on over the counter transactions, should in principle ensure that the level of frictions is kept at a minimum. Nevertheless, this is a potentially relevant aspect. Therefore, part of the analysis conducted below will involve an assessment of potential increases in the frictions to bid adjustment as a driver for the reduced pass-through.

C. Changes in the market composition and strategies

The key feature of the nuanced model illustrated above is the linkage between the electricity and ETS markets and how that can produce changes in the set of suppliers and in their strategies.

In particular, the arrival of financial players, for instance when triggered by an exogenous change in the regulatory environment, has the potential to drive the shift away from traditional producers and toward financial intermediaries, with consequences like those described above. As I will argue below, the Italian regulations in 2012 did indeed enhanced the role of financial players and this likely is a fundamental element to understand the decline in the pass-through.

D. Changes in demand

Finally, any increase in the elasticity of demand has the potential to translate into a lower pass-through. On the demand side, my empirical analysis will show that Italy experienced a change in the composition of electricity demand. Italy has seen a large increase in the share of electricity consumption by households, as apposed to industry. Labandeira (2012) shows that while large firms have highly inelastic demand, in the short run, residential consumers are much more elastic, in the short run. Therefore, the observed decreasing pass-through could instead reflect a decrease in markups from more elastic demand resulting in a further decreased pass-through. Indeed, in the Italian context this phenomenon can be associated on the one hand with the declining demand from large firms and on the other hand with the increasing number number of households purchasing electricity outside the "Single Buyer." This is clearly a substantially different explanation of the declining pass-through.

On the other hand, however, in recent years the economic crisis affecting Italy as well as most of the Western countries has contributed to the reduction of electricity demanded and emissions, thus also reducing demand for emission allowances. This has led, along with other possible factors, the decline in the price of carbon and the accumulation of a huge surplus of allowances in the system, with the risk that the EU ETS is failing to provide incentives to reduce emissions in a way efficient in terms of costs or to stimulate a low-carbon innovation. This aggregate demand force has thus also the potential to drastically reduce the need of a passing through any emissions costs if the final price of emissions is expected to be low enough.

Given this complex set of effects linked to the demand side of electricity, I will devote a substantial portion of the empirical analysis to argue why, despite the changes in demand, the pass-through decline is best understood as a change of what happened on the supply side of this market.

IV The ETS and the Italian electricity market

In this section, I present the key features of the institutional environment. First, I discuss the Italian electricity market, with a particular emphasis on the bidding system through which the electricity wholesale price is determined, and then I review the working of the ETS for carbon emissions.

IV.1 The Italian Electricity Market

In the two decades, the Italian electricity sector has been characterized by a number of institutional changes which have influenced both the competitiveness and the structure of this industry. Italy began liberalizing its electricity sector in 1999 with Legislative Decree 79/99, following European Directive 96/92/EC which establishes common rules for the generation, transmission, distribution and supply of electricity and defines, among others, the organizational and operational rules for the electricity sector and for access to the market.

The decree liberalizes generation, import, export and supply of electricity. In particular, in order to ensure competitiveness, it establishes that by January 1st 2003 anybody can either generate or import at most 50 percent of the overall energy generated and imported into Italy. For this reason, Enel, the former state monopolist, was required to sell 27 percent of its generating capacity (15,000 MWh) and to create three new independent generation companies: Elettrogen, Eurogen and Interpower.

On the demand side, the decree divides consumers into two categories: eligible customers and captive customers. An eligible customer is an individual or legal person entitled to choosing his own electricity supplier (basically any producer and wholesale customer that does not purchase electricity for his own household). From January 1st 2005, eligible customers are entitled to directly purchasing electricity on the Power Exchange (IPEX), an electronic market where wholesale electricity supply meets demand. In 2006, the amount of electricity traded on the power exchange was 196 TWh (almost 60 percent of the overall electricity purchased).

Captive customers, instead, may contract for electricity only with their local distributor. From July 1st 2004, captive customers include customers buying electricity for their own household and exclude commercial and professional activities. Their purchases from electricity producers are mediated by a company, the Single Buyer, that buys electricity both on the Power Exchange and through bilateral contracts. The purchases made by Single Buyer on the power exchange exceed 60 percent of all the transactions on this platform at the beginning of my sample. From 1st July 2007 all customers are eligible.

In this analysis, I will focus on the electricity generation sector and, in particular, on how the electricity wholesale price is formed. In particular, it is important to consider two aspects: the competitiveness of this sector and the main sources from which electricity is generated.

As regards the second aspect, in terms of generation Italy has limited energy sources and nuclear power generation was banned in a 1987 referendum. For these reasons Italy is highly dependent on energy imports. As shown in the following table, most generation comes from conventional thermal sources, with smaller amounts from hydroelectric plants and other renewables. As of 2015, about 39 percent of the total gross electricity generation is originated from renewable sources. Within this share, hydroelectric plants account for 40 percent, followed by solar power, accounting for 23 percent.[9] Among thermal sources, gas is the most prominent source: in 2006 it was 50 percent of the whole production, while in 2015 this share rose to 63 percent. Gas is followed by coal and oil: 14 percent and 11 percent respectively in 2005, while these share are 25 percent and 3 percent in 2015.[10]

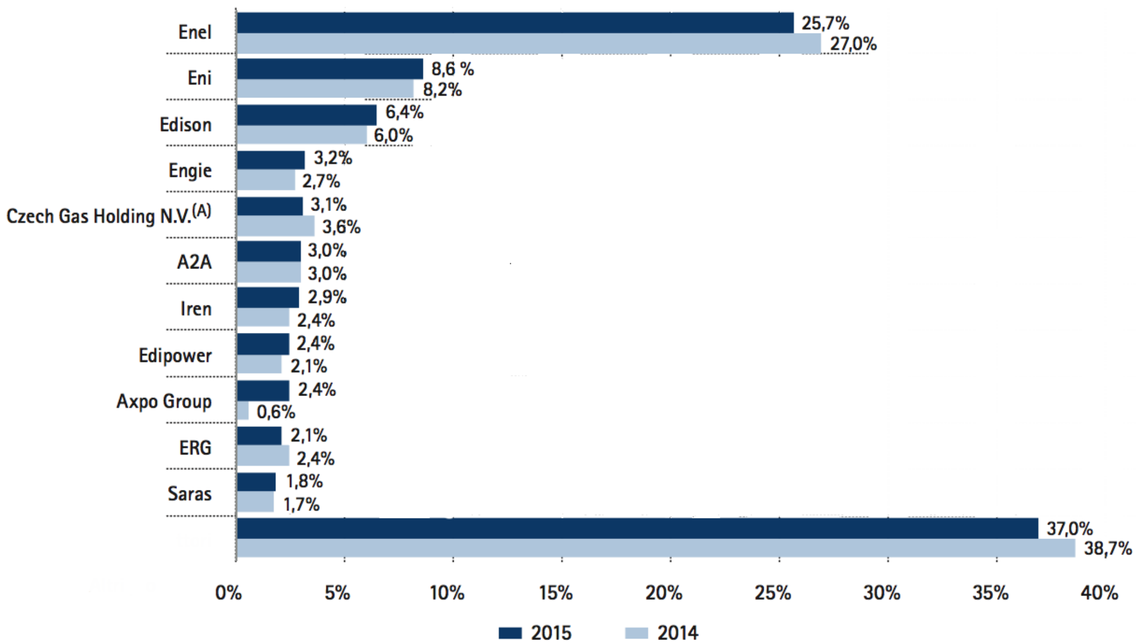
In terms of competition, throughout the sample period the market has remained rather concentrated. In 2015, 261.5 TWh of electricity were produced nationally, with Enel being the main producer (72.5 TWh), followed by Edison (18.1 TWh). Figure 3 shows who are the main electricity producers in Italy in 2014 and 2015. In both years, the top three producers are Enel, Eni and Edison. Taken together, they account for about 40 percent of the yearly electricity production, with Enel by itself accounting for a quarter of the national production. The remaining 60 percent of electricity production is distributed among a dozen of medium producers and several thousand small producers. Most of the latter producers are located in the North, with Lombardy having 2,466

[9] Italy was an early adopter of wind mills. It was the 4th largest country in terms of installed wind power capacity with 1.7 GW installed capacity by the end of 2005. As of 2015, 13 percent of all production from renewables is due to wind-based generation.

[10] Source: Authority for Gas, Electricity and Water, Annual Report 2006 and 2016 (AEEGSI, 2006 and 2016).

producers registered in 2015 according to the Authority for Gas, Electricity and Water (AEEGSI, 2016).

Figure 3: Main Producers in 2014 and 2015



List of the main producers in 2014 (light blue) and 205 (dark blue). The bars in the last row refer to the combined share of all other producers Source: elaboration from the Authority for Gas, Electricity and Water, Annual Report 2016 (AEEGSI, 2016). Note: (A) This produces was part of E.On in 2014.

These producers are the key players on the supply side of the wholesale electricity market. They participate as sellers in the trades held on the Italian Power Exchange (IPEX) where the wholesale price is set. While a few electricity exchanges take place outside the IPEX platform, the vast majority of electricity is traded on the day-ahead market. This market is open from 8am to 9.15am of the day before the electricity delivery. For every hour of the day, sellers submit a bid indicating both the quantity that they are willing to sell and the minimum unitary price they are willing to accept if their offer is accepted, in full or just for a portion of the units offered. The seller bids represent binding commitments to transfer an amount of electricity no less than what offered for at a price no higher than what requested.

Bidders enter the action knowing several publicly announced quantities: the estimated electricity demand for each geographical area, the amount of maximum allowed transit across geographical areas, the reference price that will be applied to bids that come without any specified price. After the bidding session ends, an algorithm computes the clearing price as follows: bids are ordered starting from the lowest price one and aggregating them up to form an upward sloping supply curve. The same is done for demand bids, but starting from the highest price so to form a downward sloping aggregate demand curve. The point where the two curves cross determines the equilibrium price and quantity. If the transits on the network implied by these bids do not violate the transit constraints, then the equilibrium price is unique across all geographical areas. If at least one constraint is violated, then the algorithm separates the geographical markets: one with the excess demand and one with the excess supply.[11]

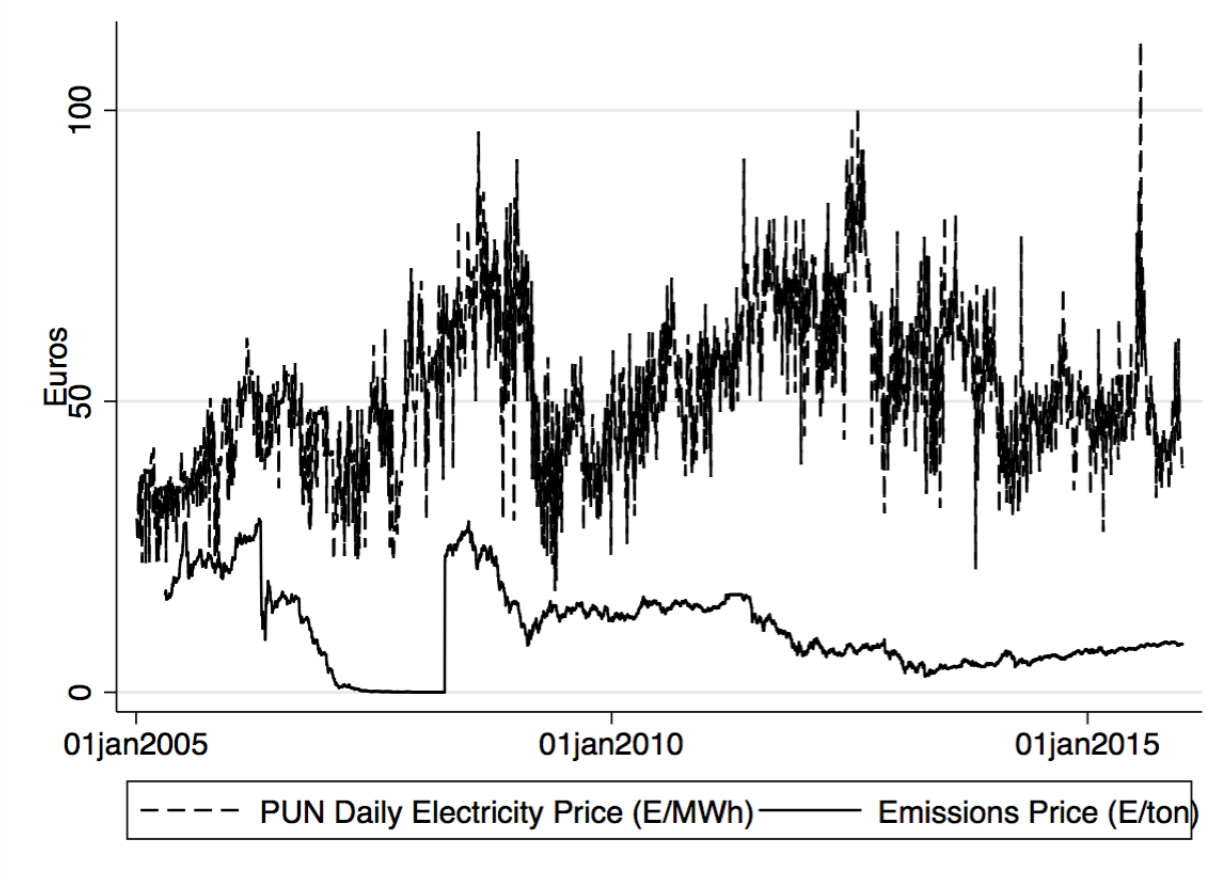
The above procedure to determine the equilibrium price is then repeated separately for each one of the geographical markets, and including in each the import/export price and quantity. The resulting prices are such that the price in the importing area is higher than that in the exporting area. The process is repeated until all transit constraints are satisfied. Therefore, the action system is an non-discriminatory auction (i.e., uniform price auction) where all sellers that bid a price at or below the equilibrium price will be paid the equilibrium price for their electricity supply. However, for the electricity destined to final consumers, there is one more step: all, potentially different, equilibrium prices arising in the six geographical areas are averaged to form the PUN (i.e., unique national price). Over the counter transaction concur to the formation of prices and they are transmitted to the IPEX in the form of bids.

In Figure 4, I plot the PUN (along with the EUA price, which is discussed next) for the sample period analyzed. The figure reveals a high degree of short run, day-to-day volatility, together with longer cycles of ups and down having roughly a three-year length. The price starts at about €30 per MWh at the beginning of the sample and gets to about €45 per MWh toward the end of the sample in 2015. I turn next to describe the ETS program and the EUA price.[12]

[11] A more detailed discussion of the various details characterizing this auction market is presented in GME (2011).

[12] For additional details on the recent trends in the Italian electricity market see also AEEGSI (2016) and GME (2016).

Figure 4: Evolution of the National Electricity Price and the EUA Price



The graph illustrates the evolution of the Italian national price (PUN) and the EUA price over the sample period.

IV.2 Characteristics of the ETS

The EU ETS is a cap-and-trade system that, starting in 2005, created the largest worldwide market for CO2 emissions. For the EU, the ETS is the main instrument to achieve the environmental goals it agreed upon under the Kyoto Protocol. In this section, I first review the basic features of the Kyoto Protocol and the discuss the details of the functioning of the ETS.

A. Brief history of the European environmental goals under the Kyoto Protocol

This idea of creating a market of rights on environmental goods, which would lead to maximization of social benefits even in the presence of externalities, led in 1997 to the subscription by more than 160 countries of the Kyoto Protocol. This international treaty on the environment established the requirement for countries developed to reduce pollutant emissions by at least 5 percent in the years 2008-2012, considering as the base year 1990.

In December 2012, with the Doha Agreement, the Protocol has been extended for another eight years, from 2012 to 2020, putting as a new objective of an overall reduction greenhouse gas emissions by 18 percent compared to 1990 levels. In 1992, during the conference in Rio de Janeiro on Environment and UN Development (Rio Earth Summit), was established the UNFCCC, the United Nations Framework Conventions on Climate Change (The United Nations Framework Convention on Climate Change), which provided for the commitment by industrialized countries in the long period of time to stabilize greenhouse gas concentrations at a level which prevents dangerous anthropogenic interference with the climate system; therefore not provide for any operative arrangement, but it represented a first step towards the resolution of the problem air pollution. On 11 December 1997, during the COP3 Conference (Conference of Parties) annual meeting of nations participating in the Climate Change Convention (UNFCCC) was agreed in Kyoto for over 160 countries, the Kyoto Protocol, treated International environmental, regarding global warming.

The treaty was opened for signature March 16, 1998, it entered into force February 16, 2005 after ratification by Russia on November 4, 2004, in accordance with Art. 25 of the same Protocol, which provided for the entry into force after ninety days from the date on which at least fifty-five Parties to the Convention (including the developed countries whose total carbon dioxide accounted for at least 55 percent of total emissions in 1990) had deposited the ratification. The Kyoto Protocol was the first treaty with legally binding thanks to which all the signatory countries undertook to pursue the objectives of tackling change climate and environmental protection, and was adopted on the basis of Art. 17 of the UNFCCC in which she was the possibility for the member states to implement protocols to pursue the objectives of the UN Convention. The Convention, in fact, not impose binding emissions limits, but provided a general commitment by the Acceding to stabilize the concentrations of greenhouse gases (carbon dioxide, methane, nitrous oxide, sulfur hexafluoride, hydrofluorocarbons and perfluorocarbons) in the atmosphere in to prevent dangerous anthropogenic interference with the climate system. For the first time compared to past conferences and agreements, the Kyoto Protocol, the CO2 reductions were legally binding on the signatory countries. The protocol included therefore, for developed countries, the obligation to make a reduction in the period 2008-2012 at least 5 percent of the polluting emissions compared to 1990.

The European Community and Member States have ratified the Protocol in May 2002 and are committed to reducing in the first five years, the emission of greenhouse gases by 8 percent compared to 1990. To pursue and stick to the target of reducing emissions of the Protocol were outlined three market instruments, so-called ”flexible mechanisms”, additional to domestic actions, through which countries Annex I of the Protocol can implement part of these target realizing projects abatement of greenhouse gas emissions where it is most convenient and economical to do it (based on the principle that it does not matter where you reduce emissions being climate change as a global problem). These three market instruments are: Joint Implementation Mechanism, Clean Development Mechanism and Emissions Trading.

The Kyoto Protocol provides for the acceding countries, a system of three mechanisms flexible to be used to the acquisition of emission credits. The first of these mechanisms, Joint Implementation (JI), is a flexible mechanism that allows the joint implementation by the countries industrialized subjected to emission constraints, addressed to the reduction of projects greenhouse gas emissions in the same annex countries (industrialized countries with economies in transition) of the Kyoto Protocol. The JI projects are defined by the Ministry Operations ”zero-sum” as the total emissions permitted in the two countries remain the themselves. The purpose of the JI mechanism is to reduce the costs of meeting the obligations Kyoto, making it possible to break down the emissions beyond where it is more cost-effective to do it.

Another flexible mechanism is represented by the development mechanisms (Clean Development Mechanism, CDM). The mechanism of Clean Development Mechanism (CDM) is one of the flexible mechanisms under the Kyoto Protocol (Art. 12), which allows companies in industrialized countries with emission limitations to implement projects aimed at reducing greenhouse gas emissions in countries developing without emission constraints. The purpose of this mechanism is twofold; on the one hand it allows countries developing to dispose of cleaner technologies and orientation towards sustainable development; the other allows the reduction of emissions where there is economically more convenient and therefore the reduction of the total cost of fulfillment of the obligations arising from the Kyoto Protocol. The emissions avoided by the realization of projects generate emission credits or CERs (Certified Emission Reductions) that can be used for compliance with the reduction commitments assigned.

The last mechanism provided by the Kyoto Protocol (Art. 17) satisfy the underwriters countries commitments that, if such measures have not been sufficient to achieve the goal, it is the international exchange of emission rights (International Emissions Trading - IET) flexible nature of environmental policy and private-voluntary, as opposed to the instruments belonging to the environmental protection traditional, command-and-control, made available to OECD countries and EIT (Economies in

B. The European Trading Scheme

The European Union Emissions Trading Scheme for Greenhouse Gases (EU ETS) is the main tool in the achievement of the Kyoto goals. It was established by the EU Directive 2003/87/EC. The scheme entails the creation of a market for CO2 emissions rights (so-called “allowances”), and its objective is to promote reductions in greenhouse gas emissions in line with the EUs commitment under the Kyoto Protocol. Europe’s commitment to the reduction of CO2 emissions has been renewed frequently since this 2003 Directive, lastly on December 2015 at the United Nations XXI annual session in Paris on climate change (COP 21) and at the XI session of the Kyoto Protocol participants. The EU ETS was, and still is, a key pillar of the EU wide strategy to curb carbon emissions.

The ETS is a cap-and-trade scheme where a central authority sets a cap on the amount of emissions, installations receive tradable allowances to emit and the overall amount of allowances cannot exceed the cap. [13] The Directive identifies the installations that are included in the emissions trading system and specifies how allowances to emit carbon dioxide are distributed among these installations. Each installation is required to have allowances equal to its total verified emissions in each calendar year.

The idea generally put forward to justify the use of such a scheme to reduce CO2 emissions is

[13]The economic insights behind the use of a cap-and-trade scheme to reduce polluting emissions are based on the ideas developed by R. H. Coase’s and extended by numerous subsequent contributions, including the vastly influential Hardin (1968)’s essay on “The tragedy of the commons,” where he developed the idea of “tradable pollution rights.”

that of maximizing efficiency. If firms are free to decide to buy and sell allowances then the firms that can achieve a reduction in their CO2 emission at a lower cost will have a greater incentive to do so than firms that that cannot reduce their emissions and, hence, prefer to buy extra allowances. Clearly, the strength of the incentives at stake depend on the price of the allowances which, in turn, is closely related to the stringency of the cap.

Annex I of the Directive indicates the industrial sectors that might be covered in the first implementation period of the ETS (phase I, from 2005 to 2007): the main sectors are power and heat generation, mineral oil refineries, iron and steel, mineral industry (cement, glass, lime, bricks, ceramics), pulp and paper. In particular, the ETS involves all combustion installations with a rated thermal input exceeding 20 MW, thus almsot the whole electricity generation sector is covered by the scheme. Altogether, this means some 12,000 installations, accounting for 45 percent of CO2 emissions in the EU. The Italian commitment is to reduce its emissions of greenhouse gases by 6.5 percent compared to 1990 levels. Each national government is required to publish a National Allocation Plan (NAP) which lists the industrial sectors involved in the scheme, the amount of emission allowances and their allocation to individual installations for each phase. Moreover, each state has the opportunity to reserve a part of the emissions to new entrants. The ETS, by including almost the entire generation sector in the EU, is likely to have a significant effect on electricity prices because of the increase in producers marginal costs due to the opportunity cost of CO2 allowances.

At the current stage, two different methods have been used to allocate emission allowances to polluting establishments: statutory assuagement and auctions. Initially, allowances have been allocated either with a grandfathering provision, where emission rights are assigned proportionally to historical emissions, or using industry benchmarks. In both cases emissions have been freely assigned. Subsequently, these approaches have been gradually been replaced by a system of auctioning off the permits. As discussed earlier, under certain conditions, in spite of whether allowances are freely distributed or whether they are auctioned at a cost, their opportunity cost should appear among the marginal costs of firms. When the actual emissions are lower than the permitted level, installations can sell the allowance in excess; conversely, when the actual emissions are higher that the permitted level, installations need to clear the gap by purchasing allowances on the allowance market from those who pollute less. Otherwise they can borrow from their allowances for the following years (if there is any year left). The scheme involves also financial penalties for non-compliance. A penalty of €40 per tonne is imposed in addition to the duty to purchase enough allowances to cover emissions.[14]

The allowances can be traded between the establishments covered by the ETS requirements, as well as between any other entity registered to trade on one of the platforms where the EUA a exchanged. The price of EUA is thus formed on a multiplicity of markets. As of 2015, the most active markets in terms of the share of transactions over the total yearly transactions of EUA are: EEX (EU t-CAP) 61 percent; EEX (DE) 24 percent; ICE (UK) 12 percent; EEX (PL t-CAP) 3 percent. In this study, I consider the EUA price from the EEX. Figure 4 shows the evolution of this price, along with that of electricity in Italy.

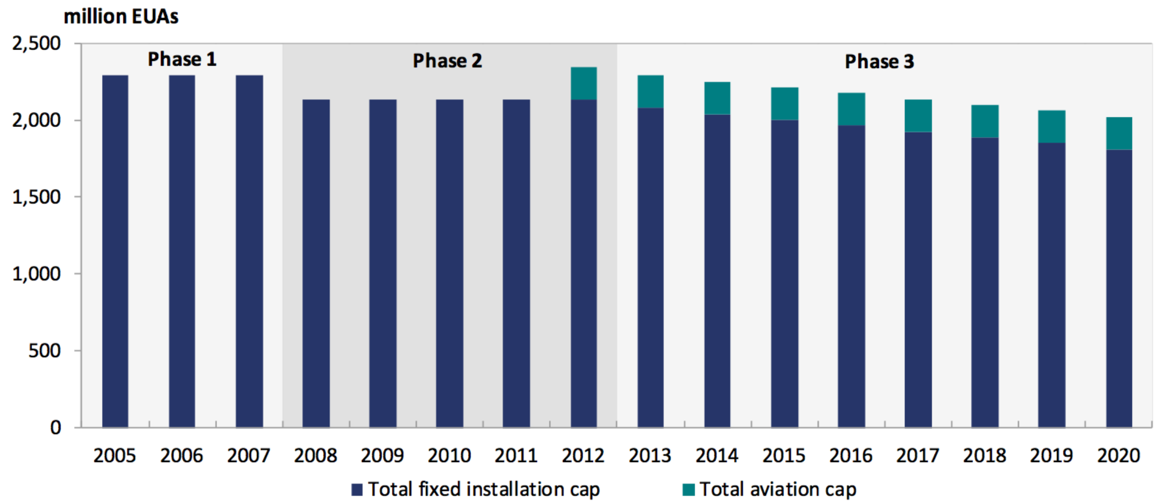
A key feature to understand the dynamic of the EUA price is that the ETS system is divided in multiple regulatory periods. We are currently in phase III and each of the three phases taking place so far had peculiarities relative to the others. Figure 5 reports the yearly cap (in million of emissions allowances) for each of the first three phases, while the key features characterizing each of these phases are briefly reviewed below.

In the first phase (2005-2007), the EU ETS included some 12,000 installations, covering mostly energy activities, production and processing of ferrous metals, mineral industry and pulp/paper. Emission allowances are only issued by national governments to installations which have a cap on their emissions under the scheme. To give an idea of the size of the market, in 2006 the trading volume was just over one billion tonnes of CO2, worth €18.1 billions.[15] Therefore, in that year the EU ETS accounted for 62 percent of the volume and 80 percent of the value of global carbon trading, making ETS the largest single market for carbon emissions. Although the quantities of EUA traded increased steadily from 2005 (799 Mt CO2), to 2007 (1.6 billion tonnes) the value of these trades was affected by the high volatility of EUA prices. In particular, as the next chapter shows, the price fluctuated widely, exceeding €30 at its peak in 2005, and then declining to about €6 toward the end of 2006, and then remaining below €1 almost always throughout 2007. This

[14]The penalty will rise to €100 per tonne in phase II.

[15]These values are taken from the web site of the market analyst, Point Carbon.

Figure 5: The Yearly CO2 Cap



For each trading phase, the figure illustrates the cap (expressed in tonnes of CO2 equivalent). This cap is how the Commission has implemented the single EU wide cap is set out in the ETS directive in terms of percentage of CO2 reductions. Source: European Commission, *ETS Handbook*, EC (2015).

price collapse can be explained by the excess of allowances given in phase I. When, in the Spring of 2006, the data on verified emissions made it clear that there was an oversupply of allowances, prices started to fall. However, back in March 2007, future prices for phase II allowances were traded at around €20 indicating that the market had expectations that the cap in phase II was going to be more stringent.

The second phase (2008-2012) expanded the scope of the scheme significantly in terms of the establishments covered. Several features of the scheme that had proved problematic during the first phase were addressed, but this did not solve all problems as evidenced by at least two factors. First, in 2009 Europol informed that 90 percent of the market volume of emissions traded in some countries could be the result of tax fraud, more specifically the, so called, "missing trader fraud," (also known as VAT or "carousel" fraud) costing governments more than 5 billion euros. The VAT fraud has been characterizing the ETS also in phase I. This fraud works as follows: a trading account is set up within one national carbon registry and is used to buy and sell EUA. EUA purchased from another country imply the generation of a tax credit, as cross-national trades do not face the VAT. These credits are then sold on in the country where the account is registered, with VAT added, but, instead of paying the VAT to the tax authorities, the traders keep it as profit made on the transaction before disappearing from where the authorities can ask the VAT back. In Italy, the fiscal treatment of sales and purchases of CO2 allowances is equivalent to that of "immaterial rights," and, hence, shall be treated exactly as transactions involving services. The fiscal treatment of services is regulated by the Decree of the President of the Republic 633 of 1972. According to this decree, the moment at which the VAT is applied is when the payment occurs, or when the receipt is emitted, whichever comes earlier. In most of the European States, the VAT treatment is similar to what described above for Italy.[16]

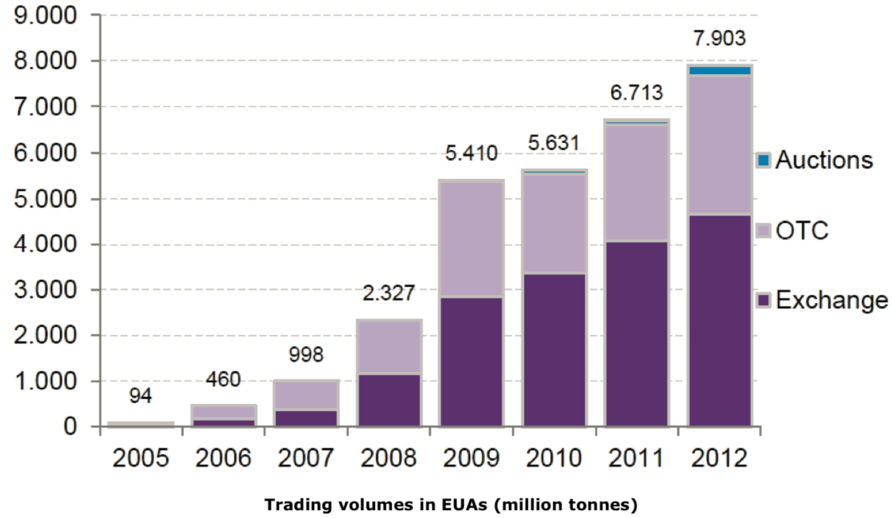
The second problem is that, also in phase II, there seems to have been an excess in allowed allocation. As for phase I, this phenomenon is associated with a marked decline (although not as abrupt as in phase I) of the EUA price. In March 2012, according to *The Economist*, the EUA permit price under the EU ETS had "tanked" and was too low to provide incentives for firms to reduce emissions. The permit price had been persistently under €10 per tonne compared to nearly €30 per tonne in 2008. The market had been oversupplied with permits. Indeed, in June 2012, EU allowances for delivery in December 2012 traded at 6.76 euros each on the ICE Futures Europe exchange, a 61 percent decline compared with the previous year.

In the third phase (2013-2020), the European Commission has proposed a number of changes, including: i) setting an overall EU cap, with allowances then allocated to EU members; ii) tighter limits on the use of offsets; iii) limiting banking of allowances between phases; iv) a move from grandfathering allowances to auctioning them. Regarding this last point, Figure 6 illustrates how, during the first two phases, allowances have been traded in roughly equal shares in over the counter (OTC) and exchanges. Only in 2012 auctions saturated to play a visible role. During 2015, Italy has awarded through such auctions 69 million of Italian EUA admissible for the phase III target. These auctions generated €528 million. This implies an average price of €7.65 per EUA which underscores an increase relative to the EUA price in the past years. This increasing trend seems to indicate that phase III will possibly not be affected by the problems of oversupply that undermined the working of the ETS market in the first two phases.

Finally, it is worth nothing that the program is intended to proceed in the foreseeable future.

[16]See Costantini et al. (2013) and DAmato, Valentini and Zoli (2017) for a more extensive discussion of the taxation issues involving the ETS and of their interactions with generators with market power..

Figure 6: Total Traded Volumes by Type of Trade



Trading volumes in million of emission allowances. Source: European Commission, *ETS Handbook*, EC (2015) and based on Bloomberg New Energy Finance figures elaborated with data from Bloomberg, ICE, Bluenext, EEX, GreenX, Climex, CCX, Greenmarket, Nordpool.

Indeed, a phase IV will commence on 1 January 2021 and finish on 31 December 2028. The European Commission plans a full review of the Directive by 2026. In fact, the reduction of at least 40 percent of gas emissions in the EU greenhouse by 2030 (compared to 1990 levels) it is one of the objectives agreed by the European Council under the 2030 framework for climate and energy. Since the EU ETS is the main instrument to achieve this goal, its reform is needed to ensure a well-functioning system. As a first step of this reform, the EU has recently taken the decision to create the reserve market stabilizer for the EU ETS. The reserve is intended to correct the huge surplus of allowances that has accumulated in the EU ETS and to make the system more resilient to imbalances between supply and demand. On 15 July 2015, the Commission submitted a second proposal, which contains a more extensive review of the EU ETS. The proposal aims to transform into law the European Council guidelines on the role that the EU ETS should play in the EU's objective of reducing greenhouse gas emissions by 2030. The proposed amendments also aim to promote innovation and the use of low-carbon technologies, helping to create new opportunities for employment and growth while maintaining the necessary safeguards to protect the industrial competitiveness in Europe.

V Data

This study is based on plant-level data for electricity supply bids and plant characteristics. The dataset collected includes information on the price of electricity in Italy and carbon emission allowances, as well as several other related information for the years from 2005 to 2015. Regarding the electricity price, the dataset contains the individual bids submitted for every hour of each day on the day-ahead segment of the Italian Power Exchange (IPEX). The source for these data is the GME, a company wholly owned by the Ministry of Economy and Finance that operates power, gas and environmental markets, including the IPEX. From the publicly available data released by the GME, I assembled a dataset containing hourly bids along with information on the identity of the power plant, its technology, its owner and the units of electricity allocated.[17] I supplemented this data with individual-level demand bid on the day-ahed market of the IPEX, price data on CO2 emissions allowances, coal, gas and oil all from Bloomberg and data on unemployment from ISTAT, the Italian statistical institute.

More in detail, the electricity bids are in the form of euro-per-MWh. These bids are submitted by the registered sellers and, together with the demand of electricity by wholesale customers, contributes to form the electricity price in the way described in the previous section. As explained there, the are six geographical areas (North, Center-north, Center-south, South, Sardinia and Sicily), each with its own, potentially different, clearing hourly-price. The analysis is conducted at the level of aggregation of the clearing bid in each geographical market/hour, however the data on the non-marginal bids will also be used to infer the degree of competition in the market.

Table 1 reports several summary statistics for the main variables used in the analysis: these are, in the order in which they appear in the table, mean, standard deviation, median, minimum, maximum and the number of observations. The table separates the data into three periods corresponding to the three phases of the ETS program. Therefore, Panel (a) contains the information for the years 2005-2007 corresponding to phase I, Panel (b) contains the information for the years 2008-2012 corresponding to phase II and Panel (c) contains the information for the years 2013-2015 corresponding to the first three years of phase III.

[17] For additional details on the data, see GME (2016).

Table 1: Summary Statistics

Panel (a): ETS Phase I (2005-2007)						
	mean	sd	p50	min	max	N
Electricity Price	72.85	40.25	69.35	0.00	417	99,734
EUA Price	12.28	10.02	14.70	0.01	29.80	99,734
Emission Intensity	1.134	0.672	1.210	0.00	2.170	99,734
Gas	58.65	7.687	59.23	30.25	91.04	93,282
Coal	49.34	6.399	48.33	37.50	62.75	99,734
Oil	65.90	10.31	63.72	46.69	95.81	99,734
Winning Operators	5.279	3.569	4.00	1.00	16.00	99,734
HHI	2,962	952.2	3,073	930	7,355	99,734
Virtual Operators	0.01	0.09	0.00	0.00	1.00	99,734
Unemployment	9.24	3.86	9.88	3.49	16.10	99,734

Panel (b): ETS Phase II (2008-2012)						
	mean	sd	p50	min	max	N
Electricity Price	72.01	41.82	68.03	0.00	450	158,766
EUA Price	12.93	5.901	13.38	0.01	29.33	158,766
Emission Intensity	1.176	0.579	1.210	0.00	2.17	158,766
Gas	50.29	13.31	55.10	17.65	100	158,766
Coal	67.35	18.53	62.20	42.20	143.2	158,766
Oil	93.28	24.30	98.74	34.04	145.7	158,766
Winning Operators	7.961	5.416	6.00	2.00	25.00	158,766
HHI	2,779	991.3	2,868	0.00	9,432	158,766
Virtual Operators	0.11	0.32	0.00	0.00	1.00	158,766
Unemployment	11.03	3.89	11.95	3.89	18.40	158,766

Panel (c): ETS Phase III (2013-2015)						
	mean	sd	p50	min	max	N
Electricity Price	56.19	26.44	54	0.00	399.0	97,876
EUA Price	6.042	1.457	6.050	2.70	8.680	97,876
Emission Intensity	1.168	0.569	1.210	0.00	2.170	97,876
Gas	52.80	12.19	49.90	29.35	97.50	97,876
Coal	52.95	6.597	53.60	40.73	64.48	97,876
Oil	86.96	26.51	102.8	34.78	119.3	97,876
Winning Operators	15.14	6.524	14.00	3.00	30.00	97,876
HHI	2,776	1,268	2,647	676	8,686	97,876
Virtual Operators	0.41	0.49	0.00	0.00	1.00	97,876
Unemployment	15.92	5.02	17.50	8.03	22.20	97,876

The table reports summary statistics for the main variables used in the analysis, separately for the three sample periods defined by the three phases of the ETS program.

The first variable of each panel, *electricity price*, is the marginal bid for each hour/geographical market. This quantity will be the main dependent variable for the subsequent analysis. The table reveals a marked difference between the average *electricity price* in the first two panels relative to that in the third: the price drops from about €72 per MWh to €56 per MWh. This decline of more than 20 percent is visible also when looking at the median price and is also accompanied by an halving of the standard deviation which passes form 41 to 26.

The main independent variable is the price of EU carbon allowances (EUA) which appears in the second row of each panel of Table 1. Allowances are the main unit traded in the ETS, and one EUA corresponds to one tonne of CO2. EUA are freely traded by all installments covered under the ETS by the National Allocation Plans, as well as by all other operators - mostly financial traders - that have obtained an EUA trading authorization.[18] The price information is at the daily level, although there are days without transactions for which the price is not reported on Bloomberg. These missing dates will be dropped from the analysis instead of implementing any imputation as, despite the relative persistence of the EUA in a narrow window of time, it would be hard to come up with credible assumptions regarding what price that the operators would have been expecting for the days with no transactions.

Regarding the value of the EUA over time, in the previous section, I described the erratic behavior of the EUA and the major price drops occurred since its introduction in 2005. In Table 1, this behavior is clear by looking at the various statistics on the EUA. During both phase I and phase II, the EUA moved between a maximum of €29 and a minimum of nearly €0, in accordance with the two market crash episodes described earlier. In both periods the average price was €12, while instead the price halves in Period III. In phase III, however, at least until the end of 2015, no additional crashes occurred and the price never went below €2.7 per tone of CO2. This pattern of similar prices between phase I and II, compared to a substantially lower, but more stable price in phase III mimics what described earlier for electricity and provides a first, descriptive evidence of the association between the electricity price and the EUA.

[18]The buying and selling takes place both on electronic markets, like the Italian IPEX, and through direct bilateral contracts (company-to-company). In the first years of the ETS program approximately one third of all exchanges were bilateral, but trading on exchanges has steadily increased over time. The main markets where spot and future contracts on EUA are traded are, along with the IPEX, the ECX (United Kingdom), the EXAA (Austria), the EEX (Germany), the PowerNext (France) and the NordPool (Norway).

The remaining rows of Table 1 report statistics for some of the most relevant control variables used in the analysis. In particular, *emission intensity* refers to the CO2 emission intensity of the generating technology used by the marginal plant. For some, typically smaller plants, there is only one type of technology, while others have multiple technologies. In the latter cases, I consider the emission intensity of the technology that is marginal. Although several plants update their technology throughout the sample, the data allows to keep track of these changes and assign to each bid its current technology. There are 14 different technologies that I observe in the sample and to each one of them I assign a value to *emission intensity* by following the European Environment Agency standards. Thus, *emission intensity* ranges from an highest factor of 2.17 for carbon based plants, to a factor of zero most of the production technologies involving renewables, which in Italy mostly involve hydric-based power generation. By comparing the three panels in Table 1, it is evident that, contrary to what observed before for *electricity price* and EUA, there is no substantial difference between the average *emission intensity* recorded in the three ETS phases. This is compatible with the lack of substantial environmental protection improvements, at least in terms of the generating technologies used.

Another set of relevant control variables involves the prices of three key inputs for the generation of electricity: coal, gas and oil. The average gas price declines between phase I and phase II. It then moderately increase again in phase III. A different pattern characterizes instead oil and coal which both experience a peak during phase II. Also peak prices of these two latter inputs are highest during phase II, in both cases exceeding 50 percent of the average price.

In addition to the cost of inputs entering the generation process, the electricity price is also potentially linked to features of the supply and demand structure. Regarding the supply factors, to control for features of the market structure I construct a variable, *winning operators* which reports the number of different operator that result to be marginal at least once in the month and geographical market considered. This variable thus proxies for the potential amount of competition. As shown in Table 1, this number grows substantially during the sample period passing from 5 operators in phase I, to 8 operators in phase II and to 15 operators in phase III. Similarly, also both the minimum and maximum number of operators increase over time. In particular, the maximum number doubles, from 16 operators in phase I to 30 in phase III.

A second measure that I use to account for the market structure is the Herfindahl-Hirschman Index (HHI). This variable measures the degree of concentration and dispersion of volumes sold by operators. The HHI is calculated, for each hour and each geographical market, as the sum of the shares of the volumes sold in the market by operators, multiplied by 100 and squared. The value of the HHI ranges between 0 (perfect competition) and 10,000 points (monopoly). The conventional threshold of 1,200 is used as the highest value compatible with a competitive market. The other threshold of 1,800, instead, is used to identify the lowest value from which a market can be considered as poorly competitive. In all three panels, the reported value of the HHI is well above 1,800, but there is nevertheless a decline over time. In particular, the median HHI passes from 3,000 in phase I to 2,600 in phase III. Thus, both HHI and *winning operators* agree to indicate a decline in suppliers' concentration over time.

In the earlier discussion about the working of the electricity market, I used Figure 3 to illustrate who who are the main electricity producers in Italy in 2014 and 2015. While Figure 3 reports the identity of the main electricity producers, it is important to point out that over time there is a declining trend in the number of trades occurring on behalf of these operators in the day-ahead market of the IPEX. To capture, this phenomenon, I construct a dummy variable, *virtual operator* that takes the value of 1 whenever the firm submitting the bid to supply the electricity has no generating capacity on its own and is not an intermediary acting on behalf of some specific producers. This variable thus captures the presence of financial traders (i.e., "virtual operators") in the electricity auctions.

As discussed when reviewing the literature, the growing role of this type of operators characterizes electricity auctions in both Europe and the US. Table 1 reveals that the extent of this phenomenon in the Italian market is absolutely relevant: while in phase I only 1 percent of the marginal bids were submitted by this type of operators, this share increases to 11 percent in phase II and it reaches a stunning 41 percent in phase III. It is also interesting to point out that there is substantial heterogeneity among these firms with some of them being large, international corporations, like Edelweiss, Dufenergy (Duferco) and Trafigura, and others being small local firms, like Enoi, Simposio and Green Trade. Simposio, in particular while being registered as a single owner, limited liability firm appears to be the marginal bidder for 11 percent of the auctions closing during in phase III.

As regards demand factors, I separately consider two sets of controls. One set includes the typical variables that are exploited in the literature to proxy for demand factors. In particular, these are the unemployment rate, to proxy for the economic conditions, and the weather conditions, to account for demand under extreme heat/cold. The second set of variables, instead, looks at the institutional features of the Italian electricity market and, in particular, at the role of the Single Buyer.

Summary statistics for the group of variables belonging to the first set are reported in Table 1. The unemployment rate is a useful proxy for the economic conditions because it can capture the demand of electricity from the corporate sector. The unemployment rate is available separately for each geographical area, but aggregated at the yearly level until 2010, while, after that date, the trimestral value is also available.[19] Specifically, the data frequency differs depending on the period considered: it is yearly in 2004 to 2009, while it becomes quarterly starting on 2010, T1 up until 2015, T4. The data are disaggregated at region, gender, age, education and unemployment duration level. I use total values (in percentage) and aggregated regions in 5 macro areas: Sicily, Sardinia, South, Center-South, Center-North and North. For each macro area / period, I averaged the unemployment level among regions.

The changes in the unemployment rate between the three phases are striking: from 9 percent in phase I, to 11 percent in phase II and to 16 percent in phase III. For this last phase, the increase in the minimum and maximum unemployment are also particularly visible, as they increase respectively to 8 percent and 22 percent. These values reflect the well known economic crisis that Italy has been facing in the recent years and that is likely to be a key driver of reduced electricity consumption from both the corporate and the residential side. Furthermore, to account for electricity demand I will also include in the regressions an interaction term between the hour of the day, the month and the geographical area. This is meant to capture the differential temperature conditions that are likely to vary between these three dimensions.

Finally, weather data has been scraped by www.ilmeteo.it at municipal/day level.[20] For each

[19]The source is the Istat, the Italian National Institute of Statistics.
[20]www.ilmeteo.it is the most important Italian weather forecasting website.

macro area, I took the daily averages of temperature and weather variables, weighted by the population at the 2011 census level. In total, the data covers 53 municipalities, including all main cities and regional administrative centers. The weather variables of interest can be grouped in 4 families: temperature, visibility, wind and rain/humidity. The first group includes *avgtempc*, *mintempc* and *maxtempc* for average, minimum and maximum temperature, respectively. The visibility (*visibilitykm*) is expressed in kilometers, whereas the wind group consists of variables on wind speed and gusts (*avgwindkmh*, *maxwindkmh* and *rafficakmh*), all reported in kilometers per hour. The latter group combines variables relative to air pressure (*pressuremb* and *avgpressuremb*) in millibars, humidity in percentage points, dew point (*puntorugiadac*) in Celsius and rain (*rainmm*) in millimeters.

Table 2: Summary Statistics: Demand Side

Panel (a): ETS Phase I (2005-2007)						
	mean	sd	p50	min	max	N
Single Buyer	45.56	15.07	45.66	8.37	81.97	99,734
Single Buyer (if >0)	45.56	15.07	45.66	8.37	81.97	99,734
Virtual Operators	2.246	2.760	1.262	0.00	17.35	99,734
Accepted Demand	99.90	0.426	100	82.33	100	99,734
Total Demand	6,417	7,203	4,017	1,083	30,804	99,734

Panel (b): ETS Phase II (2008-2012)						
	mean	sd	p50	min	max	N
Single Buyer	12.20	14.96	0.00	0.00	58.49	158,766
Single Buyer (if >0)	25.45	11.39	24.72	0.00	58.49	76,079
Virtual Operators	3.08	2.74	2.21	0.00	16.81	158,766
Accepted Demand	99.60	0.781	100	94.38	100	158,766
Total Demand	6,245	6,907	3,500	784	48,051	158,766

Panel (c): ETS Phase III (2013-2015)						
	mean	sd	p50	min	max	N
Single Buyer	3.39	7.15	0.00	0.00	46.96	97,876
Single Buyer (if >0)	13.95	7.94	12.80	0.01	46.96	23,805
Virtual Operators	8.66	5.51	7.49	0.71	36.42	97,876
Accepted Demand	90.19	8.25	91.88	52.31	100	97,876
Total Demand	6,132	7,083	3,532	786	40,835	97,876

The table reports summary statistics for the demand variables used in the analysis, separately for the three sample periods defined by the three phases of the ETS program.

Summary statistics for the second set of demand-side variables, those focused on the institutional aspects of the market, are reported in Table 2. The source for these data is the demand bid reported in the same day-ahead action data released by the IPEX. The variables that I consider describe both the total demand of electricity as well as the nature of the buyers. Analogously to what reported in the earlier table, the statistics are separated into three sample periods according to the three phases of the ETS. The total demand of electricity is measured as both the total demand (i.e., the sum of al demand bids received for every hour, day, month, year and geographical market) and the total accepted demand (expressed as a percentage of total demand). The two quantities are nearly always the same in the first two ETS phases, with an average accepted demand of 99 percent, but this value declines in phase III to 90 percent.

Marked differences across the three phases are also observed in terms of the composition of buyers. Here I consider two different variables. The first measures the share of electricity purchased by Single Buyer, both overall and conditional on its demand being positive. Regardless of which of these two measures is used, the drop in the share purchased by the Single Buyer over the three phases is evident: conditional on making any bid for the specific time/geographical market, its demand declines from 45 percent in phase I, to 25 percent in phase II to 14 percent in phase III. Since the total demand of electricity across these three phases remains substantially unaltered, this drop indicate a decline in the total demand that the Single Buyer purchased through this portion of the electricity market. The counterpart to this decline is the increase in the demand by financial operators.

Indeed, the second variable that I construct is the share of electricity demanded by operators that are the same “virtual operators” described above. Clearly these firms, by not being electricity producers, must secure their supply bids through purchases in some markets, including the demand side of the same day-ahead IPEX market. Their share, no higher than 3 percent of the total demand in the first two phases, increases to nearly 9 percent in phase III.

VI International comparison: heterogenous effects of ETS

Before beginning the empirical analysis of the ETS effects on the electricity price in Italy, it is interesting to briefly explore how the electricity market in Italy as described in the previous section compares relative to that in other countries. This is useful to understand which elements of the analysis presented in the next section will likely be more specific to the Italian context and which others, instead, will likely be more broadly applicable.

Given the complexity of both the ETS and electricity markets, my approach in this short section adopts three simplifications. First, I focus on the UK as a benchmark country for the comparison with Italy. The vast amount of data and studies on the UK market make it ideal for this purpose. Second, instead of trying to explore all possible similarities and differences, I focus exclusively on those that are more likely to induce an heterogeneous effect of the ETS on the electricity markets in Italy and the UK. Third, since the sample period covered in this study (10 years) entails several changes in both countries that would be impossible to convey in this short section, I focus on the beginning of my sample period to illustrate the initial conditions in these two markets.

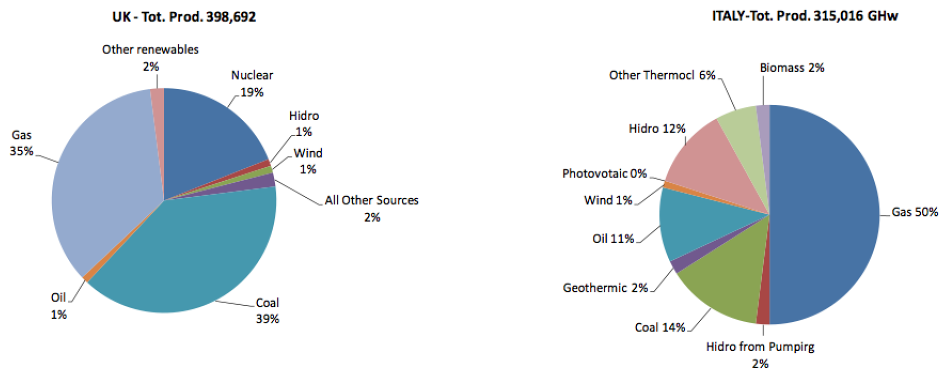
A. Different electricity production mix

One of the main differences between the production of electricity in Italy and the UK concerns the composition of the energy sources. As the pie charts presented in Figure 7 show for the period around the beginning of my sample (2006), in Italy natural gas and oil are relatively more important for indigenous production than in the UK.[21] Combined, they represent 61 percent of production in Italy, and only 36 percent in the UK. Moreover the weight of oil is almost negligible in the UK. Coal, the single most important source for the UK, is worth just 14 percent in Italy. Finally, Italy does not have nuclear plants which, instead, provide 19 percent of the electricity produced in the UK.

The descriptive evidence presented in the charts above suggests that the cost of producing electricity in Italy and in the UK is likely to respond differently to the same changes in the prices of energy sources. Since there is an interaction between the ETS and the energy prices that is possibly rather complex, depending on the amount of emissions generated by each energy source

[21] Sources for the pie charts: for Italy data from Terna S.p.A. and for UK data from BERR.

Figure 7: National Production of Electricity by Source



Note: The figure reports the breakdown by source of the total electricity produced in the UK, left, and Italy, right, near the beginning of my sample (2006).

and on the extent to which each energy source is a substitute or a complement for the others, this different energy mix is likely a potentially crucial source of heterogeneity between what I study for Italy and what could be characterizing the UK.[22]

B. Differences on the supply side: market concentration

In both Italy and the UK the production of electricity has been privatized. The market concentration, however, is rather different in the two countries. From Figure 8, we can see that toward the beginning of the sample (2006) not only does Italy have fewer big firms but, moreover, its largest producer, Enel, accounts for almost 40 percent of the production. On the contrary, the market in the UK is more evenly divided with the four largest producers all having a market share of approximately one sixth of the total market.[23]

C. Differences on the demand side: type of contracts signed

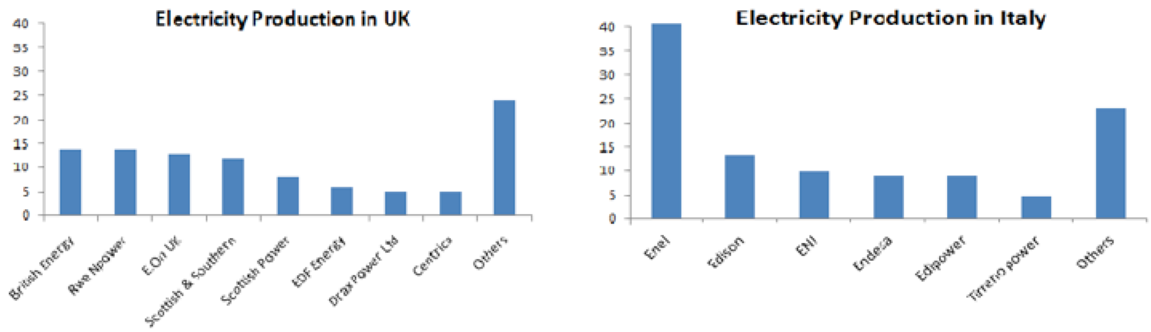
As mentioned above, in Italy the market became fully liberalized only in July 2007, while in the UK full liberalization dates back to May 1999. This difference is reflected in the still predominant role of the Single Buyer in Italy which purchases electricity for captive consumers. The presence of this large buyer, accounting for more than 60 percent of the demand toward the beginning of my sample, might be another source of greater rigidity in the Italian relative to the UK electricity market

[22] Bunn and Fezzi (2007) is an early study of the price elasticity of the UK electricity price with respect to the EUA. They find a positive, but less than one effect. On the other hand, the elasticity with respect to the price of natural gas and coal that they estimate is around one, being somewhat above or below, depending on the exact model specification.

[23] Sources for the histograms: for Italy data from AEEG annual report 2006 and for UK data from BERR (table 5.11 DUKES 2007).

contributing to explaining why carbon costs could be heterogeneously reflected in the electricity price of the two countries.

Figure 8: Market Concentration in Electricity Generation



Note: The figure reports the main national electricity producers for the UK, left, and Italy, right, near the beginning of my sample (2006).

VII Empirical strategy

The main relationship that I seek to uncover is that between changes in the electricity suppliers' bids and the EUA price. In particular, I assume that the following linear relationship exists and, using the dataset described earlier, I estimate:

$$p_{thg} = \rho \tau_t e_{thg} + \beta_1 X^D_{thg} + \beta_2 X^S_{thg} + \beta_3 I_{thg} + \varepsilon_{thg} \tag{4}$$

Where: p_{thg} is the bid of the marginal plant at hour h of day t in the geographical market g; τ_t is the price of emissions permits; e_{thg} is the emissions rate of the unit which sets the price at a given hour and geographical area; X^D_{thg} is a collection of demand factors, including economic activity indicators and weather controls; X^S_{thg} is a collection of supply factors, including fossil-fuel prices (coal, gas, and oil) interacted for whether the plant specific technology requires them for generation or not; I_{thg} are fixed effects for the geographical market, the month, day of the week and hour. These fixed fixed effects are aimed to control for potential trends and fluctuations that are time or space specific.

The parameter of interest is ρ, the coefficient describing the linear relationship between the electricity price offered by an establishment and the product between the world price of EUA and the plant-specific CO2 emission intensity. The hypothesis that I want to test is whether the price of the EUA is passed on to the price of electricity. A ρ close to one would support the idea of a complete pass-through which, as discussed earlier, is important both to assess the degree of competitiveness in the Italian electricity market and to understand the impacts of the ETS in this market more broadly. In an ideal environment, I would be able to observe random variation in the EUA price, holding fixed the level of emission intensity. This would allow me to trace out ρ from the variations in p_{thg} associated with these hypothetical variations in the EUA price.

What I observe in the GSE data, however, differs form this ideal situation and, hence, the empirical strategy proposed tries to correct for departures from this ideal. The first element of this strategy consists of estimating the above relationship through OLS in which the set of included covariates is gradually expanded. In particular, I always include fixed effects for the year, month, day and hour, as well as controls for the price of coal, gas and oil, all multiplied for a dummy for whether the technology of the plant involves consuming such input. Since the electricity price depends on both demand and supply factors, I use controls that account for both. For electricity demand, I include the unemployment rate and fixed effects for the interaction between the hour of the day, the month and the geographical area. For supply, I include the number of different marginal operators in the month and geographical area. I also consider specifications including a rich set of measures of the weather conditions that capture both demand (this is the case of the temperature) and supply (this is the case of the wind speed and amount of precipitations) features. In some specifications, I also include fixed effects for the plant submitting the bid.

The second element of the empirical strategy follows an instrumental variables approach for the identification of ρ. In addition to the usual concerns about omitted variables, the presence of a bias in the OLS estimate of ρ is due to the specific interaction of the ETS with the different generating sources. As pointed out by Fabra and Reguant (2014), an endogeneity bias in the OLS estimates might be driven by unobserved supply and demand shocks. As the main variation in emissions rates comes from the different technologies used, with carbon being the most emission intense, but coal plants also tending to have lower marginal costs than gas plants, one runs the risk of mistakenly associating low electricity prices to high values of $\tau_t * e_{th}$. That is, whenever carbon will be the marginal technology, the electricity price will typically be low, but $\tau_t * e_{th}$ will tend to be high. The OLS would thus result in a low, potentially negative, relationship between electricity price and $\tau_t * e_{th}$. The sign of the bias is thus unambiguous: the OLS is downward biased and fixing this bias requires the use of an instrument.

As proposed by Fabra and Reguant (2014), I use the emissions price τ_t as an instrument. The idea behind the validity of this instrument is that τ_t is, in an obvious way, correlated with $\tau_t * e_{th}$ and, likely, also exogenous to the price set by the Italian electricity bidders. The reason for the latter claim being that the EUA are traded at the European level by a worldwide set of operators, including all establishments covered by the ETS (which go well beyond the electricity sector) as well as a broad array of financial traders. The presence of both these types of companies that are unrelated to the Italian electricity sector makes particularly unlikely that their bid and ask positions in the EUA market are affected by the same factors driving the price choice of the firms bidding to sell electricity on the IPEX day-ahead market. This latter claim, however, might become less adequate in the latter years of the sample when, as I will discuss below, the role of financial players, possibly taking simultaneously different positions in the electricity and EUA markets might imply that this latter price no longer moves exogenously relative to the electricity price in in Italy. Aside from this potentially problematic role of financial operators relative to the effectiveness of the proposed IV strategy, note that even if some common factors might be present between the actions in these two markets, the presence of a rich set of covariates is likely able to control for them.

In addition to the arguments above, the validity of the proposed instrument can be also evaluated through the inspection of the first stage and reduced form regressions. For the first stage regression, the model to be estimated is:

$$\tau_t e_{thg} = \rho^{FS} e_{thg} + \beta_1 X^D_{thg} + \beta_2 X^S_{thg} + \beta_3 I_{thg} + \varepsilon_{thg}, \tag{5}$$

where the notation used is the same illustrated regarding equation (4). A strong first stage should lead to the estimation of a positive and statistically significant coefficient ρ^{FS}. Given that the instrument is an element in the product $\tau_t * e_{thg}$, this strong relationship is likely to be mechanically satisfied.

The reduced form regression to be estimated is:

$$p_{thg} = \rho^{RF} e_{thg} + \beta_1 X^D_{thg} + \beta_2 X^S_{thg} + \beta_3 I_{thg} + \varepsilon_{thg}, \tag{6}$$

where, the main dependent variable is now the EUA price. Once again, we expect a positive and significant coefficient on ρ^{RF} confirming that the instrument is mechanically associated in a strong way with the electricity price.

Finally, it is worth mentioning two additional problems with the OLS approach to the pass-through identification which have been highlighted by a recent study of MacKay et al. (2014). This study argues that, even under standard orthogonally conditions, where observed cost measures are uncorrelated with other cost drivers, it may not be possible to obtain consistent estimates from reduced form regressions of price on cost. In particular if the economics environment is not characterized by constant pass-through then two biases arise.

The first, misspecification bias, occurs when pass-through varies with cost and the cost distribution is skewed. This misspecification bias exists even when all relevant variables are observed perfectly but can be corrected for (by using splines or higher order polynomials). The second, partial information, bias is of concern when pass-through depends on the cost and only part of marginal cost is observable and the unobserved component of marginal cost is correlated with the observed component. While independence of unobservable cost from observed cost may be too strong an assumption, the authors provide bounds for the second form of bias that can be calculated from underlying demand system and under plausible assumptions on the cost distribution.

These considerations are important because the potentially changing degree of market power during the sample analyzed might be a source of non-constant pass-through. In this respect, my strategy is to subdivide the sample in three main periods and to separately perform the regressions presented above for each of them. The large sample size in each phase ensures that this strategy does not imply a substantial loss in the precision of the estimates. Moreover, since the exact sample split that I use is based on subdividing the data according to the three regulatory periods of the ETS (phases I, II and III), this strategy also alleviates the concern that the results might be confounded by pooling together data that pertain to rather different regulatory environments.

VIII Results

In this section, I first present the baseline results that I obtain from the instrumental variable strategy. Then, I address their robustness relative to several variations related to the instrument, the model specification and the data sample.

VIII.1 Baseline results

The first set of results that I present regards the OLS estimates of the model in equation (4). Table 3 presents these estimates in three separate panels corresponding to a temporal data split of the sample according to the three regulatory periods of the ETS. Therefore, panel (a) involves only data for the years from 2005 to 2007 (phase I), panel (b) covers the years from 2008 to 2012 (phase II) and panel (c) covers the years from 20013 to 2015 (the first three years of phase III).

All specifications include controls for the price of coal, gas and oil, all multiplied by a dummy for whether the technology of the plant involves consuming such input. Always included are also fixed effects for the geographical market, the year, the month, the day and the hour. No other controls are included in model (1). Model (2) adds to model (1) controls for electricity demand: the unemployment rate and fixed effects for the interaction between the hour of the day, the month and the geographical area. Model (3) adds to model (2) a control for electricity supply: winning operator, the number of different marginal operators in the month and geographical area. The last three columns are identical to the first three with the addition of fixed effects for identity of the plant submitting the bid.

The main result that forcefully appears from Table 3 is that the pass-through estimates obtained via OLS is highly sensitive to the sample period and model specification used. Across sample periods, the estimates range from being at (or even above) one (panel (b) and (c), column (1)), to being next to zero (either a statistically significant low value, as in the last three columns of panel (a), or an insignificant low value, as in panel (a) columns (2) and (3) and panel (c), columns (5) and (6)). Relative to the most parsimonious specification (column (1)), the addition of covariates tends to lead to a decrease in the magnitude of the coefficient. This feature is particularly noticeable in panels (b) and (c). In these latter two panels, there is indeed a wide variation in the estimate of ρ across the different model specifications. In contrast, in panel (a) these estimates are nearly unaffected by the model specification.

Table 3: Electricity Price Pass-through Estimates: OLS Regressions

Panel (a): ETS Phase I (2005-2007)

OLS	(1)	(2)	(3)	(4)	(5)	(6)
Mg. emissions costs (ρ)	0.08*	0.04	0.04	0.08***	0.07***	0.07***
	(0.04)	(0.03)	(0.03)	(0.02)	(0.02)	(0.02)
Observations	99,734	99,734	99,734	99,706	99,706	99,706
R-squared	0.60	0.73	0.73	0.70	0.80	0.80
Input price (coal, gas, oil)	Yes	Yes	Yes	Yes	Yes	Yes
Time FE (yr, mo, dy, hr)	Yes	Yes	Yes	Yes	Yes	Yes
Demand controls	No	Yes	Yes	No	Yes	Yes
Supply controls	No	No	Yes	No	No	Yes
Plant FE	No	No	No	Yes	Yes	Yes

Panel (b): ETS Phase II (2008-2012)

OLS	(1)	(2)	(3)	(4)	(5)	(6)
Mg. emissions costs (ρ)	1.08***	0.71***	0.69***	0.44***	0.37***	0.37***
	(0.06)	(0.06)	(0.06)	(0.10)	(0.08)	(0.08)
Observations	158,766	158,766	158,766	158,728	158,728	158,728
R-squared	0.44	0.60	0.60	0.67	0.73	0.73
Input price (coal, gas, oil)	Yes	Yes	Yes	Yes	Yes	Yes
Time FE (yr, mo, dy, hr)	Yes	Yes	Yes	Yes	Yes	Yes
Demand controls	No	Yes	Yes	No	Yes	Yes
Supply controls	No	No	Yes	No	No	Yes
Plant FE	No	No	No	Yes	Yes	Yes

Panel (c): ETS Phase III (2013-2015)

OLS	(1)	(2)	(3)	(4)	(5)	(6)
Mg. emissions costs (ρ)	1.84***	0.82***	0.83***	-0.11	-0.06	-0.05
	(0.67)	(0.30)	(0.30)	(0.17)	(0.14)	(0.15)
Observations	97,876	97,876	97,876	97,809	97,809	97,809
R-squared	0.27	0.52	0.53	0.65	0.71	0.71
Input price (coal, gas, oil)	Yes	Yes	Yes	Yes	Yes	Yes
Time FE (yr, mo, dy, hr)	Yes	Yes	Yes	Yes	Yes	Yes
Demand controls	No	Yes	Yes	No	Yes	Yes
Supply controls	No	No	Yes	No	No	Yes
Plant FE	No	No	No	Yes	Yes	Yes

Note: *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Standard errors clustered by year and geographical market in parenthesis. The dependent variable is *electricity price*, the marginal bid. The main independent variable is *erateeprice*, the product of the EUA price and the plant's emission intensity. The different columns report the OLS regression estimate for *erateeprice* on *electricity price*. The model specification changes across columns. All specifications include controls for the price of coal, gas and price, all multiplied for a dummy for whether the technology of the plant involves consuming such input. Always included are also fixed effects for the year, month, day and hour. No other controls are included in model (1). Model (2) adds to model (1) controls for electricity demand: the unemployment rate and fixed effects for the interaction between the hour of the day, the month and the geographical area. Model (3) adds to model (2) a control for electricity supply: *winning operator*, the number of different marginal operators in the month and geographical area. The last three columns are identical to the first three with the addition of fixed effects for the unit submitting the bid.

In particular, the inclusion of plant level fixed effects (latter three columns), has a relevant effect on the magnitude of the estimated ρ in panels (b) and (c), but not in panel (a). Focusing on the most complete model, column (6), the estimate is 7 percent for phase I, 37 percent for phase II and zero (i.e., a -5 percent estimate, but not statistically different from zero) for phase III. As argued earlier, the OLS estimates are likely to be biased downward and, indeed, for the case of Spain, Fabra and Reguant (2014) present OLS estimates for phase I that are negative. In their case, the IV estimates reverted this result and lead to a large and positive estimated pass-through of about 80 percent. The IV results that I present below will achieve something similar for phase I, but not for the other phases. However, before turning to the IV results, I report below the first stage and reduced form estimates.

In terms of the first stage equation (5), I present the corresponding estimates in Table 4. The estimates are organized in the same way as those in the previous table. Contrary to the previous table, however, the first stage regressions reveal a great deal of stability across both time periods and specification models. All estimated coefficients range between 1.04 and 1.22 and they are all statistically significant at the 1 percent level. Also the explained variance of the various models is similar and rather high as illustrated by the R^2 values reported in the table. All these results are coherent with the mechanical relationship between the chosen instrument and the product $\tau_t * e_{th}$.

Next, I turn to the reduced form estimates which are reported in Table 5. These are the estimates corresponding to equation (6). This table presents are more mixed evidence across the three phases. In phase I, all estimates are positive, statistically significant and ranging in a relatively narrow interval between 0.78 and 0.89. In phase II, all estimates are again positive, statistically significant and concentrated within a narrow range, but this time the range is between 0.34 and 0.58. FInally, in phase III, all estimates are negative, but not statistically different from zero. These estimates imply that my IV approach is not an effective strategy to estimate the pass-through for phase III. This is rather surprising since the same model specifications are implemented for phase III relative to the other phases. Indeed, the explained variance remains fairly similar across the estimates in the three panels, with the exception of column (1) of panel (c) where we observe a substantially lower R^2 relative to the other models. This is coherent with several forces that I explore in great detail in the next section.

Table 4: IV Strategy: First Stage

Panel (a): ETS Phase I (2005-2007)

	(1)	(2)	(3)	(4)	(5)	(6)
EUA Price	1.17***	1.17***	1.17***	1.20***	1.20***	1.20***
	(0.04)	(0.03)	(0.04)	(0.04)	(0.04)	(0.04)
Observations	99,734	99,734	99,734	99,706	99,706	99,706
R-squared	0.57	0.59	0.59	0.63	0.64	0.64
Input price (coal, gas, oil)	Yes	Yes	Yes	Yes	Yes	Yes
Time FE (yr, mo, dy, hr)	Yes	Yes	Yes	Yes	Yes	Yes
Demand controls	No	Yes	Yes	No	Yes	Yes
Supply controls	No	No	Yes	No	No	Yes
Plant FE	No	No	No	Yes	Yes	Yes

Panel (b): ETS Phase II (2008-2012)

	(1)	(2)	(3)	(4)	(5)	(6)
EUA Price	1.08***	1.07***	1.07***	1.04***	1.04***	1.05***
	(0.06)	(0.06)	(0.06)	(0.05)	(0.05)	(0.05)
Observations	158,766	158,766	158,766	158,728	158,728	158,728
R-squared	0.73	0.76	0.77	0.81	0.81	0.81
Input price (coal, gas, oil)	Yes	Yes	Yes	Yes	Yes	Yes
Time FE (yr, mo, dy, hr)	Yes	Yes	Yes	Yes	Yes	Yes
Demand controls	No	Yes	Yes	No	Yes	Yes
Supply controls	No	No	Yes	No	No	Yes
Plant FE	No	No	No	Yes	Yes	Yes

Panel (c): ETS Phase III (2013-2015)

	(1)	(2)	(3)	(4)	(5)	(6)
EUA Price	1.19***	1.18***	1.18***	1.21***	1.22***	1.22***
	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)
Observations	97,876	97,876	97,876	97,809	97,809	97,809
R-squared	0.76	0.78	0.78	0.84	0.85	0.85
Input price (coal, gas, oil)	Yes	Yes	Yes	Yes	Yes	Yes
Time FE (yr, mo, dy, hr)	Yes	Yes	Yes	Yes	Yes	Yes
Demand controls	No	Yes	Yes	No	Yes	Yes
Supply controls	No	No	Yes	No	No	Yes
Plant FE	No	No	No	Yes	Yes	Yes

Note: *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Standard errors clustered by year and geographical market in parenthesis. The dependent variable is *erateeprice*, the product of the EUA price and the plant's emission intensity. The main independent variable is the EUA price. The different columns report the OLS regression estimate for the EUA price on *erateeprice*. The model specification changes across columns. All specifications include controls for the price of coal, gas and price, all multiplied for a dummy for whether the technology of the plant involves consuming such input. Always included are also fixed effects for the year, month, day and hour. No other controls are included in model (1). Model (2) adds to model (1) controls for electricity demand: the unemployment rate and fixed effects for the interaction between the hour of the day, the month and the geographical area. Model (3) adds to model (2) a control for electricity supply: *winning operator*, the number of different marginal operators in the month and geographical area. The last three columns are identical to the first three with the addition of fixed effects for the unit submitting the bid.

Table 5: IV Strategy: Reduced Form

Panel (a): ETS Phase I (2005-2007)

	(1)	(2)	(3)	(4)	(5)	(6)
EUA Price	0.89***	0.85***	0.86***	0.80***	0.78***	0.78***
	(0.19)	(0.09)	(0.10)	(0.09)	(0.05)	(0.06)
Observations	99,734	99,734	99,734	99,706	99,706	99,706
R-squared	0.60	0.74	0.74	0.70	0.80	0.80
Input price (coal, gas, oil)	Yes	Yes	Yes	Yes	Yes	Yes
Time FE (yr, mo, dy, hr)	Yes	Yes	Yes	Yes	Yes	Yes
Demand controls	No	Yes	Yes	No	Yes	Yes
Supply controls	No	No	Yes	No	No	Yes
Plant FE	No	No	No	Yes	Yes	Yes

Panel (b): ETS Phase II (2008-2012)

	(1)	(2)	(3)	(4)	(5)	(6)
EUA Price	0.58***	0.51***	0.52***	0.35***	0.34***	0.34***
	(0.17)	(0.17)	(0.15)	(0.13)	(0.10)	(0.10)
Observations	158,766	158,766	158,766	158,728	158,728	158,728
R-squared	0.41	0.58	0.59	0.67	0.73	0.73
Input price (coal, gas, oil)	Yes	Yes	Yes	Yes	Yes	Yes
Time FE (yr, mo, dy, hr)	Yes	Yes	Yes	Yes	Yes	Yes
Demand controls	No	Yes	Yes	No	Yes	Yes
Supply controls	No	No	Yes	No	No	Yes
Plant FE	No	No	No	Yes	Yes	Yes

Panel (c): ETS Phase III (2013-2015)

	(1)	(2)	(3)	(4)	(5)	(6)
EUA Price	-0.67	-0.77	-0.84	-0.54	-0.46	-0.55
	(0.51)	(0.51)	(0.55)	(0.41)	(0.37)	(0.54)
Observations	97,876	97,876	97,876	97,809	97,809	97,809
R-squared	0.25	0.52	0.53	0.65	0.71	0.71
Input price (coal, gas, oil)	Yes	Yes	Yes	Yes	Yes	Yes
Time FE (yr, mo, dy, hr)	Yes	Yes	Yes	Yes	Yes	Yes
Demand controls	No	Yes	Yes	No	Yes	Yes
Supply controls	No	No	Yes	No	No	Yes
Plant FE	No	No	No	Yes	Yes	Yes

Note: *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Standard errors clustered by year and geographical market in parenthesis. The dependent variable is *electricity price*, the marginal bid. The main independent variable is the EUA price. The different columns report the OLS regression estimate for the EUA price on *electricity price*. The model specification changes across columns. All specifications include controls for the price of coal, gas and price, all multiplied for a dummy for whether the technology of the plant involves consuming such input. Always included are also fixed effects for the year, month, day and hour. No other controls are included in model (1). Model (2) adds to model (1) controls for electricity demand: the unemployment rate and fixed effects for the interaction between the hour of the day, the month and the geographical area. Model (3) adds to model (2) a control for electricity supply: *winning operator*, the number of different marginal operators in the month and geographical area. The last three columns are identical to the first three with the addition of fixed effects for the unit submitting the bid.

Several insights from the discussion above are further strengthened by the IV estimates reported in Table 6. The IV coefficient, which are simply the ratio of the reduced form and first stage coefficients for this situation with one single instrument, are as expected: positive and statistically significant in phase I, with the magnitude of the phase I estimates being between 50 and 100 greater than that of the corresponding phase II estimates (i.e., for the same model specification). The estimates for phase III, instead, are never statistically significant.

For the estimates in panel (a) and (b), the addition of covariates to the model specification reduces the magnitude of the estimated coefficient. Nevertheless, in the case of phase I, the estimates obtained are all contained in a relatively narrow interval between 0.65 and 0.76. Thus, even the lowest of these estimates would indicate a non-negligible degree of pass-through. This magnitude is indeed closer to the 80 percent estimated by Fabra and Reguant (2014) than to the often extremely low pass-through estimates of the earlier literature, referenced in the earlier review. Indeed, the 95 percent confidence interval estimate for all the six models in panel (a) includes the value of the point estimate obtained by Fabra and Reguant (2014) for Spain during nearly the same time span.

Nevertheless, the fact that over the three regulatory periods the estimated pass-through gradually declines, first halving in phase II relative to phase I and then reaching a value not statistically different from zero in phase III is indicative of relevant changes in the market. As evidenced above, the driver of this difference is the reduced form relationship linking the electricity price to the EUA price. Below I analyze a series of channels that might be responsible for the change over time in this relationship. Before that, however, I conclude this section with a series of robustness checks for the baseline estimates presented in this section.

Table 6: Electricity Price Pass-through Estimates: IV Regressions

Panel (a): ETS Phase I (2005-2007)

	(1)	(2)	(3)	(4)	(5)	(6)
Mg. emissions costs (ρ)	0.76***	0.73***	0.73***	0.66***	0.65***	0.65***
	(0.15)	(0.08)	(0.09)	(0.08)	(0.04)	(0.04)
Observations	99,734	99,734	99,734	99,706	99,706	99,706
R-squared	0.56	0.70	0.70	0.68	0.78	0.78
Input price (coal, gas, oil)	Yes	Yes	Yes	Yes	Yes	Yes
Time FE (yr, mo, dy, hr)	Yes	Yes	Yes	Yes	Yes	Yes
Demand controls	No	Yes	Yes	No	Yes	Yes
Supply controls	No	No	Yes	No	No	Yes
Plant FE	No	No	No	Yes	Yes	Yes

Panel (b): ETS Phase II (2008-2012)

	(1)	(2)	(3)	(4)	(5)	(6)
Mg. emissions costs (ρ)	0.54***	0.48***	0.49***	0.33***	0.33***	0.33***
	(0.14)	(0.13)	(0.12)	(0.11)	(0.10)	(0.10)
Observations	158,766	158,766	158,766	158,728	158,728	158,728
R-squared	0.43	0.59	0.60	0.67	0.73	0.73
Input price (coal, gas, oil)	Yes	Yes	Yes	Yes	Yes	Yes
Time FE (yr, mo, dy, hr)	Yes	Yes	Yes	Yes	Yes	Yes
Demand controls	No	Yes	Yes	No	Yes	Yes
Supply controls	No	No	Yes	No	No	Yes
Plant FE	No	No	No	Yes	Yes	Yes

Panel (c): ETS Phase III (2013-2015)

	(1)	(2)	(3)	(4)	(5)	(6)
Mg. emissions costs (ρ)	-0.56	-0.65	-0.71	0.45	0.38	-0.45
	(0.11)	(0.44)	(0.46)	(0.33)	(0.31)	(0.37)
Observations	97,876	97,876	97,876	97,809	97,809	97,809
R-squared	0.24	0.51	0.52	0.65	0.71	0.71
Input price (coal, gas, oil)	Yes	Yes	Yes	Yes	Yes	Yes
Time FE (yr, mo, dy, hr)	Yes	Yes	Yes	Yes	Yes	Yes
Demand controls	No	Yes	Yes	No	Yes	Yes
Supply controls	No	No	Yes	No	No	Yes
Plant FE	No	No	No	Yes	Yes	Yes

Note: *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Standard errors clustered by year and geographical market in parenthesis. The dependent variable is *electricity price*, the marginal bid. The main independent variable is *erateeprice*, the product of the EUA price and the plant's emission intensity. The different columns report the IV regression estimated via 2SLS for *erateeprice* on *electricity price*, where the instrument is the EUA price. The model specification changes across columns. All specifications include controls for the price of coal, gas and price, all multiplied for a dummy for whether the technology of the plant involves consuming such input. Always included are also fixed effects for the year, month, day and hour. No other controls are included in model (1). Model (2) adds to model (1) controls for electricity demand: the unemployment rate and fixed effects for the interaction between the hour of the day, the month and the geographical area. Model (3) adds to model (2) a control for electricity supply: *winning operator*, the number of different marginal operators in the month and geographical area. The last three columns are identical to the first three with the addition of fixed effects for the unit submitting the bid.

VIII.2 Robustness

In this subsection, I present a series of results analyzing the robustness of the previous baseline estimates to a series of modifications. First of all, I am interested in exploring the statistical validity of the instrument and the potential for bias in the IV estimates. Second, I am interested in the robustness of the estimates to the inclusion in the specification of additional controls for demand and supply related to weather conditions that were originally excluded from the baseline specifications in order to make them more parsimonious. Third, I will explore the sensitivity of the estimates to different sample splits. In particular, those sample splits involving the distinction between peak and non-peak electricity demand as well as those concerned with separating marginal bids of plants with different technologies.

I begin the assessment of the baseline estimates by presenting in Table 7 the values of the F statistic for the first stage model, along with other measures of fit pertaining to this model. In particular, all the statistics in the table are computed with regard to the first stage regression corresponding to model (1) of the IV estimates reported in Table 6. Thus, the first row in the table corresponds to the regression model of column (1) in panel (a) Table 6, the second row corresponds to column (1) in panel (b) of Table 6 and the third row corresponds to column (1) in panel (c) Table 6. Not surprisingly given the mechanical association between the proposed instrument and the variable to be instrumented, the observed value of the F is very high, ranging from about 300 to nearly 3,000, all values well above the typically used rule of thumb value of 10 derived from Stock and Yogo and that, if not reached, would signal a problem of weak instrument.

Importantly, the results in Table 7 indicate that across the three phases there is no particular reason to worry about a weakening of the instrument strength, so that this is an unlikely channel to explain the drop in the IV estimates described with regard to the baseline estimates. In accordance with these results, Table 8 reports LIML (limited information maximum likelihood) estimates that are essentially identical to those obtained via the 2SLS used for the baseline estimates. In the presence of weak instruments, the bias of the IV estimator would move the 2SLS estimate closer to the (biased) OLS estimate relative to the LIML estimate. Thus, observing nearly identical 2SLS and LIML estimates confirms that a problem of weak instrument is not a concern.

Table 7: Instrument Performance

	R^2	Adjusted R^2	Partial R^2	Robust F	$Prob > F$
Phase I	0.572	0.571	0.106	872	0.000
Phase II	0.733	0.733	0.404	313	0.000
Phase III	0.758	0.758	0.078	2,969	0.000

Note: the table reports the key first stage statistics to assess the instrument performance. All the statistics are computed with regard to the first stage regression corresponding to model (1) of the IV estimates reported in Table 6. Thus, the first row in the table corresponds to the regression model of column (1) in panel (a) Table 6, the second row corresponds to column (1) in panel (b) Table 6 and the third row corresponds to column (1) in panel (c) Table 6.

Table 8: Electricity Price Pass-through Estimates: IV Regressions (LIML)

Panel (a): ETS Phase I (2005-2007)

	(1)	(2)	(3)	(4)	(5)	(6)
Mg. emissions costs (ρ)	0.76***	0.73***	0.73***	0.66***	0.65***	0.65***
	(0.15)	(0.08)	(0.09)	(0.08)	(0.04)	(0.04)
Observations	99,734	99,734	99,734	99,706	99,706	99,706
R-squared	0.56	0.70	0.70	0.68	0.78	0.78
Input price (coal, gas, oil)	Yes	Yes	Yes	Yes	Yes	Yes
Time FE (yr, mo, dy, hr)	Yes	Yes	Yes	Yes	Yes	Yes
Demand controls	No	Yes	Yes	No	Yes	Yes
Supply controls	No	No	Yes	No	No	Yes
Plant FE	No	No	No	Yes	Yes	Yes

Panel (b): ETS Phase II (2008-2012)

	(1)	(2)	(3)	(4)	(5)	(6)
Mg. emissions costs (ρ)	0.54***	0.48***	0.49***	0.33***	0.33***	0.33***
	(0.14)	(0.13)	(0.12)	(0.11)	(0.10)	(0.10)
Observations	158,766	158,766	158,766	158,728	158,728	158,728
R-squared	0.43	0.59	0.60	0.67	0.73	0.73
Input price (coal, gas, oil)	Yes	Yes	Yes	Yes	Yes	Yes
Time FE (yr, mo, dy, hr)	Yes	Yes	Yes	Yes	Yes	Yes
Demand controls	No	Yes	Yes	No	Yes	Yes
Supply controls	No	No	Yes	No	No	Yes
Plant FE	No	No	No	Yes	Yes	Yes

Panel (c): ETS Phase III (2013-2015)

	(1)	(2)	(3)	(4)	(5)	(6)
Mg. emissions costs (ρ)	-0.56	-0.65	-0.71	0.45	0.38	-0.45
	(0.42)	(0.44)	(0.46)	(0.33)	(0.31)	(0.37)
Observations	97,876	97,876	97,876	97,809	97,809	97,809
R-squared	0.24	0.51	0.52	0.65	0.71	0.71
Input price (coal, gas, oil)	Yes	Yes	Yes	Yes	Yes	Yes
Time FE (yr, mo, dy, hr)	Yes	Yes	Yes	Yes	Yes	Yes
Demand controls	No	Yes	Yes	No	Yes	Yes
Supply controls	No	No	Yes	No	No	Yes
Plant FE	No	No	No	Yes	Yes	Yes

Note: *** p<0.01, ** p<0.05, * p<0.1. Standard errors clustered by year and geographical market in parenthesis. The dependent variable is *electricity price*, the marginal bid. The main independent variable is *erateeprice*, the product of the EUA price and the plant's emission intensity. The different columns report the IV regression estimated via LIML for *erateeprice* on *electricity price*, where the instrument is the EUA price. The model specification changes across columns. All specifications include controls for the price of coal, gas and price, all multiplied for a dummy for whether the technology of the plant involves consuming such input. Always included are also fixed effects for the year, month, day and hour. No other controls are included in model (1). Model (2) adds to model (1) controls for electricity demand: the unemployment rate and fixed effects for the interaction between the hour of the day, the month and the geographical area. Model (3) adds to model (2) a control for electricity supply: *winning operator*, the number of different marginal operators in the month and geographical area. The last three columns are identical to the first three with the addition of fixed effects for the unit submitting the bid.

The next set of robustness checks involves gradually expanding the set of controls included in the model specification in order to account for additional demand and supply factors. In Table 9, I report a series of regressions all based on an extension of the most saturated model of the baseline regressions (i.e., model (6) of Table 6). In particular, column (1) of Table 9 is the same as column (6) in Table 6 and is reported only to ease the comparison with the following five models.

The following five columns augment the model of column (1) by gradually introducing (first, sequentially one at a time, and then altogether) the four groups of variables related to weather that I collect (for temperature, rain, visibility and wind). More specifically, column (2) includes temperature measures: average, minimum and maximum daily temperature across the major cities in the relevant geographical area. Column (3), instead, adds rain data: air pressure (pressuremb and avgpressuremb) in millibars, humidity in percentage points, dew point (puntorugiadac) in Celsius and rain (rainmm) in millimeters. Column (4), uses visibility (visibilitykm) which is a measure of visibility expressed in kilometers. Then, column (5) includes wind-related measures: wind speed and gusts (avgwindkmh, maxwindkmh and rafficakmh), all reported in kilometers per hour. Finally, column (6) includes simultaneously in the specification all these weather measures.

The results reported in Table 9 reveal that, despite the rich set of demand and supply factors that these additional weather variables are in principle able to capture, the baseline estimates are essentially unchanged. For some specifications, this table presents slightly lower point estimates of ρ than those in Table 6. Nevertheless, the differences are minor and the confidence interval of the baseline estimates always includes the corresponding point estimates in Table 9. Most crucially, Table 9 confirms the heterogeneity of the pass-through estimates across the three sample periods. This is indicative that what might explain such differences is not related to demand fewtures that can be accounted for by weather conditions or by supply forces linked to the strength of green technologies (as proxies by the intensity of winds and precipitations).

Table 9: Electricity Price Pass-through Estimates: IV Regressions with Weather Controls

Panel (a): ETS Phase I (2005-2007)

	(1)	(2)	(3)	(4)	(5)	(6)
Mg. emissions costs (ρ)	0.65***	0.65***	0.63***	0.64***	0.63***	0.63***
	(0.04)	(0.04)	(0.03)	(0.04)	(0.04)	(0.03)
Observations	99,706	94,779	94,543	94,755	94,731	94,471
R-squared	0.78	0.78	0.78	0.78	0.78	0.78
Temperature	No	Yes	No	No	No	Yes
Rain	No	No	Yes	No	No	Yes
Visibility	No	No	No	Yes	No	Yes
Wind	No	No	No	No	Yes	Yes

Panel (b): ETS Phase II (2008-2012)

	(1)	(2)	(3)	(4)	(5)	(6)
Mg. emissions costs (ρ)	0.33***	0.33***	0.31***	0.30***	0.30***	0.26**
	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)
Observations	158,728	156,953	157,885	154,353	157,861	153,435
R-squared	0.73	0.73	0.73	0.73	0.73	0.72
Input price (coal, gas, oil)	Yes	Yes	Yes	Yes	Yes	Yes
Temperature	No	Yes	No	No	No	Yes
Rain	No	No	Yes	No	No	Yes
Visibility	No	No	No	Yes	No	Yes
Wind	No	No	No	No	Yes	Yes

Panel (c): ETS Phase III (2013-2015)

	(1)	(2)	(3)	(4)	(5)	(6)
Mg. emissions costs (ρ)	-0.45	-0.42	-0.48	-0.59	-0.48	-0.61
	(0.37)	(0.36)	(0.36)	(0.36)	(0.36)	(0.34)
Observations	97,809	96,847	97,634	94,777	97,634	94,007
R-squared	0.71	0.71	0.71	0.71	0.72	0.71
Input price (coal, gas, oil)	Yes	Yes	Yes	Yes	Yes	Yes
Temperature	No	Yes	No	No	No	Yes
Rain	No	No	Yes	No	No	Yes
Visibility	No	No	No	Yes	No	Yes
Wind	No	No	No	No	Yes	Yes

Note: *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Standard errors clustered by year and geographical market in parenthesis. The dependent variable is *electricity price*, the marginal bid. The main independent variable is *erateeprice*, the product of the EUA price and the plant's emission intensity. The different columns report the IV regression estimated via 2SLS for *erateeprice* on *electricity price*, where the instrument is the EUA price. The model specification changes across columns. All specifications include controls for the price of coal, gas and price, all multiplied for a dummy for whether the technology of the plant involves consuming such input. Always included are also fixed effects for the year, month, day and hour. The regression model reported in column (1) is the same of column (6) in Table 6. The following columns augment this same model by gradually introducing (first, sequentially one at a time, and then altogether) the four groups of variables related to weather described in the main text: temperature, rain, visibility and wind.

The third and last set of robustness checks involves two different sample splits. In the first one, as conventional in the literature, I consider the possibility of differences between peak and non peak times. In Table 10, columns (1) and (2) include all data and are identical to columns (1) and (6) of Table 6. Columns (3) and (4) report the estimate of the two models of the first two columns, but on the subsample of peak time bids (i.e., electricity bids for the weekdays, from Mondays to Fridays, in the interval between 8am and 8pm). Columns (5) and (6) report the estimate of the two models of the first two columns, but on the subsample of off-peak time bids.

The results in Table 10 clearly indicate that the point estimate of ρ is systematically higher for peak relative to off-peak hours, albeit the difference is not particularly small and tends to be not statistically significant. Most importantly, the same broad patterns that we had described with regard to the baseline estimates and, in particular, the fact that the estimated ρ is well below one in all three sample periods and tends to decline substantially moving from older years toward more recent ones, is clearly present both for peak and off-peak electricity price bids.

The second sample split that I consider entails repeating the IV estimates above, but limiting the sample to carbon emitting sources. While the EUA price enters the optimal pricing problem as a marginal cost only for those CO2-emitting plants under the ETS, the EUA price might also affect bidding by establishments not covered by the ETS. In an imperfectly competitive world with firms that own multiple plants, this can happen for at least two reasons.

First, if the same firm has within the same market both establishments covered and not covered by the ETS, then its pricing choice for the non-covered plants will incorporate how this choice affects its overall profitability through the price and quantities sold by all its plants, including those covered by the ETS, and hence directly affected by the ETS. Second, even for firms not covered by the ETS, the fact that their competitors are subject to cost changes linked to (observable) EUA price variations should induce a strategic response to take advantage of the changes in the cost effectiveness of the rivals. These two effects, however, are both a consequence of the first order effect that we shall see the EUA price imposes on the electricity price offered by ETS-covered establishments.

Therefore, a first sanity check for the above baseline estimates consists of repeating the IV estimates exclusively for those plants covered by the ETS. The idea behind this test is that if the effects estimated in Table 6 are originated from the bids submitted by non-ETS covered plants, then the data are inconsistent with the effect of the EUA price described above. The results are reported in Table 11, which involves the same model specifications as in Table 6, but estimated only on the subsample of bids originating from plants that emit some positive level of C02 when producing electricity.

Aside from a reduction of the magnitude of ρ relative to Table 6 that involves nearly all models and sample periods, the qualitative take away from this table is the same of Table 6: a markup that is below 1 already in phase I and that afterwards declines steeply in phases II and III. Since the estimates obtained in Table 11 are all similar, albeit smaller than those obtained in Table 6, this is indicative of the presence of some strategic effects complementing the direct effects, as one would indeed expect in an environment with market power.

Table 10: Electricity Price Pass-through Estimates: All, Peak, Off-peak

Panel (a): ETS Phase I (2005-2007)

	(1) All	(2) All	(3) Peak	(4) Peak	(5) Off-peak	(6) Off-peak
Mg. emissions costs (ρ)	0.76***	0.65***	0.87***	0.74***	0.60***	0.52***
	(0.15)	(0.04)	(0.18)	(0.06)	(0.14)	(0.03)
Observations	99,734	99,706	54,164	54,143	45,570	45,533
R-squared	0.56	0.78	0.29	0.64	0.53	0.77
Input price (coal, gas, oil)	Yes	Yes	Yes	Yes	Yes	Yes
Time FE (yr, mo, dy, hr)	Yes	Yes	Yes	Yes	Yes	Yes
Demand controls	No	Yes	No	Yes	No	Yes
Supply controls	No	Yes	No	Yes	No	Yes
Plant FE	No	Yes	No	Yes	No	Yes

Panel (b): ETS Phase II (2008-2012)

	(1) All	(2) All	(3) Peak	(4) Peak	(5) Off-peak	(6) Off-peak
Mg. emissions costs (ρ)	0.54***	0.33***	0.77***	0.51***	0.24	0.09
	(0.14)	(0.10)	(0.12)	(0.11)	(0.18)	(0.10)
Observations	158,766	158,728	92,316	92,286	66,450	66,418
R-squared	0.43	0.73	0.60	0.69	0.44	0.77
Input price (coal, gas, oil)	Yes	Yes	Yes	Yes	Yes	Yes
Time FE (yr, mo, dy, hr)	Yes	Yes	Yes	Yes	Yes	Yes
Demand controls	No	Yes	No	Yes	No	Yes
Supply controls	No	Yes	No	Yes	No	Yes
Plant FE	No	Yes	No	Yes	No	Yes

Panel (c): ETS Phase III (2013-2015)

	(1) All	(2) All	(3) Peak	(4) Peak	(5) Off-peak	(6) Off-peak
Mg. emissions costs (ρ)	-0.56	-0.44	-0.15	-0.14	-1.14***	-0.76**
	(0.42)	(0.37)	(0.63)	(0.48)	(0.30)	(0.30)
Observations	97,876	97,809	54,366	54,298	43,510	43,447
R-squared	0.24	0.71	0.23	0.69	0.26	0.74
Input price (coal, gas, oil)	Yes	Yes	Yes	Yes	Yes	Yes
Time FE (yr, mo, dy, hr)	Yes	Yes	Yes	Yes	Yes	Yes
Demand controls	No	Yes	No	Yes	No	Yes
Supply controls	No	Yes	No	Yes	No	Yes
Plant FE	No	Yes	No	Yes	No	Yes

Note: *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Standard errors clustered by year and geographical market in parenthesis. The dependent variable is *electricity price*, the marginal bid. The main independent variable is *erateeprice*, the product of the EUA price and the plant's emission intensity. The different columns report the IV regression estimated via 2SLS for *erateeprice* on *electricity price*, where the instrument is the EUA price. The model specification changes across columns. All specifications include controls for the price of coal, gas and price, all multiplied for a dummy for whether the technology of the plant involves consuming such input. Always included are also fixed effects for the year, month, day and hour. Columns (1) and (2) include all data and are identical to columns (1) and (6) of Table 6. Columns (3) and (4) report the estimate of the two models of the first two columns, but on the subsample of peak time bids (i.e., electricity bids for the weekdays in the interval between 8am and 8pm). Columns (5) and (6) report the estimate of the two models of the first two columns, but on the subsample of off-peak time bids.

Table 11: Electricity Price Pass-through Estimates: IV Regressions, Carbon Emitting Bidders Only

Panel (a): ETS Phase I (2005-2007)

	(1)	(2)	(3)	(4)	(5)	(6)
Mg. emissions costs (ρ)	0.58***	0.51***	0.51***	0.46***	0.43***	0.43***
	(0.15)	(0.09)	(0.09)	(0.07)	(0.04)	(0.05)
Observations	77,190	77,190	77,190	77,169	77,169	77,169
R-squared	0.56	0.73	0.73	0.71	0.81	0.81
Input price (coal, gas, oil)	Yes	Yes	Yes	Yes	Yes	Yes
Time FE (yr, mo, dy, hr)	Yes	Yes	Yes	Yes	Yes	Yes
Demand controls	No	Yes	Yes	No	Yes	Yes
Supply controls	No	No	Yes	No	No	Yes
Plant FE	No	No	No	Yes	Yes	Yes

Panel (b): ETS Phase II (2008-2012)

	(1)	(2)	(3)	(4)	(5)	(6)
Mg. emissions costs (ρ)	0.66***	0.56***	0.55***	0.34**	0.32***	0.32***
	(0.11)	(0.10)	(0.10)	(0.12)	(0.09)	(0.09)
Observations	134,801	134,801	134,801	134,776	134,776	134,776
R-squared	0.50	0.64	0.64	0.72	0.77	0.77
Input price (coal, gas, oil)	Yes	Yes	Yes	Yes	Yes	Yes
Time FE (yr, mo, dy, hr)	Yes	Yes	Yes	Yes	Yes	Yes
Demand controls	No	Yes	Yes	No	Yes	Yes
Supply controls	No	No	Yes	No	No	Yes
Plant FE	No	No	No	Yes	Yes	Yes

Panel (c): ETS Phase III (2013-2015)

	(1)	(2)	(3)	(4)	(5)	(6)
Mg. emissions costs (ρ)	-0.95**	-0.85**	-0.92**	-0.53	-0.41	-0.49
	(0.34)	(0.35)	(0.56)	(0.30)	(0.23)	(0.28)
Observations	97,876	83,519	83,519	83,472	83,472	83,472
R-squared	0.24	0.55	0.56	0.65	0.72	0.72
Input price (coal, gas, oil)	Yes	Yes	Yes	Yes	Yes	Yes
Time FE (yr, mo, dy, hr)	Yes	Yes	Yes	Yes	Yes	Yes
Demand controls	No	Yes	Yes	No	Yes	Yes
Supply controls	No	No	Yes	No	No	Yes
Plant FE	No	No	No	Yes	Yes	Yes

Note: *** p<0.01, ** p<0.05, * p<0.1. Standard errors clustered by year and geographical market in parenthesis. The dependent variable is *electricity price*, the marginal bid. The main independent variable is *erateeprice*, the product of the EUA price and the plant's emission intensity. The different columns report the IV regression estimated via 2SLS for *erateeprice* on *electricity price*, where the instrument is the EUA price. The model specification changes across columns. All specifications include controls for the price of coal, gas and price, all multiplied for a dummy for whether the technology of the plant involves consuming such input. Always included are also fixed effects for the year, month, day and hour. No other controls are included in model (1). Model (2) adds to model (1) controls for electricity demand: the unemployment rate and fixed effects for the interaction between the hour of the day, the month and the geographical area. Model (3) adds to model (2) a control for electricity supply: *winning operator*, the number of different marginal operators in the month and geographical area. The last three columns are identical to the first three with the addition of fixed effects for the unit submitting the bid.

IX What explains the drop in the pass-through?

In the last part of Section 3, I discussed four sets of drivers that might be behind the decline in the pass-through revealed by the estimates in the previous section. These four forces regard changes in both supply and demand. Although identifying a unique channel for this effect is likely impossible given the many, complex interactions present in this market, the goal of this section is to shed light on those element for which the data gives more clear indications about their relevance (or lack of relevance) to explain the drop in the pass-through. I analyze each of the four potential drivers in the same order in which they were presented in Section 3. The main result will be that it is not a change in the market power of electricity generators per se to have produced this effect, but likely it is the combined effect of changes in market power occurring both in the electricity and the ETS market and that, at least in part, are linked to the regulatory changes implemented by Italy in 2012 which bolstered the role of financial operators.

IX.1 Changes in the suppliers market power

The first channel that I analyze is that of changes in the suppliers' market power. As discussed in Section 3, increases in market power would reduce the pass-through. The exact extent of the reduction would depend on the nature of the change in market power. To a first extent, however, the direction of the change in the pass-through will be the same regardless of whether such increase emerges from a reduction in the number of suppliers, from a concentration in the market shares of the existing producers or from more collusive behavior. Therefore, I proceed by discussing sequentially each of these three factors.

The first and most simple variable to look at is the number of potential competitors, as measured through the variable *winning operators* presented in Section V. As discussed earlier, however, the number of potential competitors is increasing over time, thus going against the idea of a possible increase of market power through this channel. In particular, as reported in the summary statistics (Table 1), *winning operators*, which reports the number of different firms setting at least one marginal bid in the relevant market, grows over time passing from 5 firms in phase I to 8 firms in phase II and then to 15 firms in phase III.[24]

A second measure that I consider is the HHI. This seems more promising, at least judging on the basis of the summary statistics in Table 1. In this case, in fact, although the passage from phase I to phase II indicates a small drop in the HHI (from 2,962 to 2,779), at least with the passage to phase III we do not observe any further decline in market power (the HHI remains nearly identical at 2,776), as, instead, indicated by the number of winning firms measure.

Nevertheless, also the HHI fails to indicate a clear pattern toward greater concentration that could explain the evidence in the baseline regressions for phase III. To better understand the potential relevance of the HHI to contribute to the interpretation of the declining pass-through, I repeat the baseline estimates now partitioning the sample according to the realizations of the HHI.

Table 12 reports the estimates obtained with either the most parsimonious specification of the baseline estimates (column (1) of Table 6), odd numbered columns, or the most saturated specification (column (6) of Table 6), even numbered columns, for three different subsamples differing for their HHI: columns (1) and (2) report the estimates on the subsample of competitive markets (i.e., $HHI < 1200$); columns (3) and (4) report the estimates on the subsample of moderately concentrated markets (i.e., $1800 > HHI \geq 1200$); columns (5) and (6) report the estimates on the subsample of highly concentrated markets (i.e., $HHI \geq 1800$).

The results in Table 12 indicate essentially that, while in phase I and II the association of greater market power with lower pass-through is confirmed, phase III appears unusual in a way that is not explained by the differences in market concentration. More in detail, during phase I it is evident that for each one of the two specifications the ranking of the coefficients is monotonic in the HHI with the least saturated specification indicating a pass-through that declines from 0.93 to 0.74 and the most saturated specification indicating a decline from 0.74 to 0.62. The estimates are always statistically significant at the 5 percent level and, in some, but not all cases, the standard errors are tight enough so that we can reject that, for instance, that the estimate in model (2) is within a 95 percent confidence interval of the estimate in column (6).

In phase II, the estimates in panel (b) reveal a similar situation, albeit only for the markets

[24] Relatedly, also the maximum of *winning operators* increases: from 16 operators in phase I to 30 in phase III.

with an $HHI \geq 1200$. The pass-through is also estimated to be lower than that of phase I and especially so for the most concentrated markets, where the estimated coefficient in model (6) is roughly halved passing from phase I to phase II. For the markets with $HHI < 1200$, instead, the estimates are not statistically significant. This latter result is fully driven by the inclusion of the 2012 year of data, as the last year of phase II. Removing the observations for 2012 makes the estimated coefficients of models (1) and (2) statistically significant and equal to about 0.74. When comparing the HHI across the years, however, nothing special emerges concerning 2012, confirming that changes in the HHI are unable to explain the changes in the pass-through.

Most interestingly, for phase III the distinction between different levels of the HHI has absolutely no bite to explain the zero pass-through indicated by most of the estimates obtained for this sample period. Indeed, for five of the six models estimated the coefficient is not statistically significant and, typically, highly so. In the only case where it is significant, model (4), its negative value of -1.80 makes it an implausible estimate for the pass-through. Therefore, it appears that changes in market concentration by themselves are an unlikely explanation for the evolution of the pass-through rate.

Table 12: Electricity Price Pass-through Estimates: Market Concentration

Panel (a): ETS Phase I (2005-2007)

	(1) $HHI < 1200$	(2) $HHI < 1200$	(3) $HHI \geq 1200$ $HHI < 1800$	(4) $HHI \geq 1200$ $HHI < 1800$	(5) $HHI \geq 1800$	(6) $HHI \geq 1800$
Mg. emissions costs (ρ)	0.93**	0.74*	0.81***	0.68***	0.74***	0.62***
	(0.15)	(0.18)	(0.11)	(0.02)	(0.12)	(0.06)
Observations	3,517	3,485	12,619	12,541	83,575	83,473
R-squared	0.60	0.82	0.62	0.82	0.56	0.78
Input price (coal, gas, oil)	Yes	Yes	Yes	Yes	Yes	Yes
Time FE (yr, mo, dy, hr)	Yes	Yes	Yes	Yes	Yes	Yes
Demand controls	No	Yes	No	Yes	No	Yes
Supply controls	No	Yes	No	Yes	No	Yes
Plant FE	No	Yes	No	Yes	No	Yes

Panel (b): ETS Phase II (2008-2012)

	(1) $HHI < 1200$	(2) $HHI < 1200$	(3) $HHI \geq 1200$ $HHI < 1800$	(4) $HHI \geq 1200$ $HHI < 1800$	(5) $HHI \geq 1800$	(6) $HHI \geq 1800$
Mg. emissions costs (ρ)	-1.41	-1.59	0.69**	0.72***	0.56***	0.32**
	(0.63)	(0.59)	(0.27)	(0.21)	(0.22)	(0.13)
Observations	11,447	11,409	17,386	17,218	129,870	129,797
R-squared	0.33	0.72	0.47	0.74	0.44	0.74
Input price (coal, gas, oil)	Yes	Yes	Yes	Yes	Yes	Yes
Time FE (yr, mo, dy, hr)	Yes	Yes	Yes	Yes	Yes	Yes
Demand controls	No	Yes	No	Yes	No	Yes
Supply controls	No	Yes	No	Yes	No	Yes
Plant FE	No	Yes	No	Yes	No	Yes

Panel (c): ETS Phase III (2013-2015)

	(1) $HHI < 1200$	(2) $HHI < 1200$	(3) $HHI \geq 1200$ $HHI < 1800$	(4) $HHI \geq 1200$ $HHI < 1800$	(5) $HHI \geq 1800$	(6) $HHI \geq 1800$
Mg. emissions costs (ρ)	-1.46	-0.72	-2.27	-1.80**	-0.54	-0.22
	(1.21)	(1.40)	(1.11)	(0.56)	(0.42)	(0.38)
Observations	8,334	8,233	19,904	19,760	69,580	69,472
R-squared	0.47	0.73	0.22	0.73	0.24	0.73
Input price (coal, gas, oil)	Yes	Yes	Yes	Yes	Yes	Yes
Time FE (yr, mo, dy, hr)	Yes	Yes	Yes	Yes	Yes	Yes
Demand controls	No	Yes	No	Yes	No	Yes
Supply controls	No	Yes	No	Yes	No	Yes
Plant FE	No	Yes	No	Yes	No	Yes

Note: *** p<0.01, ** p<0.05, * p<0.1. Standard errors clustered by year and geographical market in parenthesis. The dependent variable is *electricity price*, the marginal bid. The main independent variable is *erateeprice*, the product of the EUA price and the plant's emission intensity. The different columns report the IV regression estimated via 2SLS for *erateeprice* on *electricity price*, where the instrument is the EUA price. The model specification changes across columns. All specifications include controls for the price of coal, gas and price, all multiplied for a dummy for whether the technology of the plant involves consuming such input. Always included are also fixed effects for the year, month, day and hour. Odd numbered columns have a specification identical to column (1) of Table 6, while even numbered columns have a specification identical to column (6) of Table 6. Columns (1) and (2) report the estimates on the subsample of competitive markets (i.e., $HHI < 1200$); columns (3) and (4) report the estimates on the subsample of moderately concentrated markets (i.e., $1800 > HHI \geq 1200$); columns (5) and (6) report the estimates on the subsample of highly concentrated markets (i.e., $HHI \geq 1800$).

Regarding collusion, although no direct evidence of detected collusion in this market is available, the electricity auctions are a market that satisfies many of the conditions typically seen as conducive to collusion (Porter and Zona, 1993). Indeed, the same firms repeatedly interact in the same auctions, electricity is a fully homogenous product, the demand for electricity is rather predictable and, for each firm, changes in the generating capacity are easily observable to other firms. Therefore it appears relevant to discuss to what extent the data reveal changes in phase III that might be compatible with an expansion of collusive bidding relative to the previous two phases.

However, a first look at the data to identify anomalies in price levels and variance (in the spirit of the mean-variance screening tests of Abrantes-Metz and Bajari, 2010) indicates that phase III does not look more likely to be affected by collusion than the two earlier phases. As reported in Table 2, while the standard deviation of the marginal bid goes down in phase III (from about 40 to 26), so does the average price (from 72 to 56). Indeed, the coefficient of variation across the three phases remains fairly similar at about 0.5. Hence, this simple test does not reveal a variance drop indicative of increased collusive behavior.

A second assessment that I perform entails looking at asymmetric changes of the pass-through in response to increases or decreases of the emission allowances price. In Table 13, I report the results of the IV regression obtained by estimating the most saturated model of Table 6 (i.e., in column (6)) on different partitions of the data based on the direction of the allowances price change. All odd numbered columns in Table 13 restrict the sample to trading days when there is a positive change in the price of the EUA (i.e., the price in that day is higher than the one in the previous day).[25] Even numbered columns, instead, are based on data from trading days when the EUA price declines relative to the previous day. The table also reports sub partitions of the data to separate peak time bids (i.e., electricity bids for the weekdays in the interval between 8am and 8pm) from off-peak time bids.

The estimate reveal some, fairly limited differences between upward and downward instances of the allowances price change: phase I is, as usual, the one for which the economic interpretation of the estimates seems the least controversial. As in the "rockets and feeders literature" (Peltzman,

[25]Qualitatively similar results to the ones abstained with this definition were also found with alternative definitions of the variable. For instance, I experimented with looking at lagging the variable described in the text by one day.

2000, and Tappata, 2010) discussed in Section 3, there is an higher pass-through when firms have to pass cost increases than when they have to pass cost decreases. As the various columns of panel (a) indicate, this is true for both the whole sample and, individually, for each of the peak vs. off-peak sub-partitions. During phase II and III, however, the sign and magnitude of the estimated coefficients change in way that challenge any simple interpretation. In general, however, it seems clear that controlling for potential collusion does not lead to a solution to the anomalies in the phase III pass-through. Perhaps this is not surprising given the results of Venditti (2010). This study finds that in Italy both petrol and diesel prices, sectors relatively close to electricity, there is not much asymmetry in the direction of the pass-through. For both petrol and diesel prices a similar result to that found for Italy is also for three other the large euro-area countries (Germany, France and Spain).

Table 13: Evidence on Asymmetric Pass-through: Upward vs. Downward EUA Price Changes

Panel (a): ETS Phase I (2005-2007)

	(1)	(2)	(3)	(4)	(5)	(6)
Electricity Hour Bid:	All	All	Peak	Peak	Off-peak	Off-peak
EUA Price Change:	Upward	Downward	Upward	Downward	Upward	Downward
Mg. emissions costs (ρ)	0.75***	0.53***	0.93***	0.68***	0.53***	0.37***
	(0.08)	(0.02)	(0.06)	(0.05)	(0.07)	(0.03)
Observations	22,542	25,133	12,218	13,649	10,292	11,448
R-squared	0.78	0.84	0.61	0.73	0.78	0.81

Panel (b): ETS Phase II (2008-2012)

	(1)	(2)	(3)	(4)	(5)	(6)
Electricity Hour Bid:	All	All	Peak	Peak	Off-peak	Off-peak
EUA Price Change:	Upward	Downward	Upward	Downward	Upward	Downward
Mg. emissions costs (ρ)	-0.14	0.10	0.12	0.13	-0.49**	-0.34*
	(0.20)	(0.23)	(0.23)	(0.29)	(0.21)	(0.15)
Observations	41,284	44,349	24,030	25,837	17,232	18,471
R-squared	0.75	0.75	0.73	0.73	0.78	0.77

Panel (c): ETS Phase III (2013-2015)

	(1)	(2)	(3)	(4)	(5)	(6)
Electricity Hour Bid:	All	All	Peak	Peak	Off-peak	Off-peak
EUA Price Change:	Upward	Downward	Upward	Downward	Upward	Downward
Mg. emissions costs (ρ)	-1.00*	0.09	-0.66	0.80	-1.40**	-0.80**
	(0.53)	(0.37)	(0.65)	(0.43)	(0.53)	(0.31)
Observations	29,829	25,129	16,551	13,919	13,201	11,123
R-squared	0.74	0.73	0.73	0.71	0.76	0.76

Note: *** p<0.01, ** p<0.05, * p<0.1. Standard errors clustered by year and geographical market in parenthesis. The dependent variable is *electricity price*, the marginal bid. The main independent variable is *erateeprice*, the product of the EUA price and the plant's emission intensity. The different columns report the IV regression estimated via 2SLS for *erateeprice* on *electricity price*, where the instrument is the EUA price.Across all columns, the model specification is identical and corresponds to that in column (6) of Table 6 (i.e., the most saturated model). Across the different columns, what changes is the sample analyzed. All odd numbered columns restrict the sample to trading days when there is a positive change in the price of the EUA (i.e., the price in that day is higher than the one in the previous day). Even numbered columns, instead, are based on data from trading days when the EUA price declines relative to the previous day. Columns (1) and (2) include all data. Columns (3) and (4) report the estimate of the two models of the first two columns, but on the subsample of peak time bids (i.e., electricity bids for the weekdays in the interval between 8am and 8pm). Columns (5) and (6) report the estimate of the two models of the first two columns, but on the subsample of off-peak time bids.

IX.2 Changes in frictions

A change in the ease with which firms can adjust their price offers would be a straightforward explanation for changes in the pass-through rate. However, the public exchange on which electricity is traded makes price change frictions an unlikely feature of this market. Furthermore, a careful review of the rules under which this market operates does not reveal any institutional change that could justify an increase in frictions.

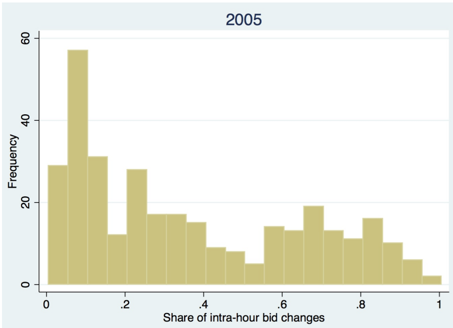
Nevertheless, to try to empirically substantiate the view that frictions did not increase over time, I exploit the observability of the identity of the plant bidding to quantify the frequency with which each plant updates its bid. A slowing down in this rate would be compatible with an increase in frictions. In particular, to obtain a (rough) measure of the relevance of price rigidities in this market, I look at how frequently a plant changes its price bid from one hour to the next, relative to all the ids submitted by the plant. Figure 9 reports the histogram of the distribution obtained. The plots report, separately for each year in the sample, for each bidding plant the share of its bids entailing a price change relative to the following hour of the same day (until 11pm), out of all the plant's bids. The more the histogram is concentrated on values close to zero, the more rare is for a plant to change its bid from one hour to the next and, hence, the more price frictions might be present. On the contrary, an histogram mostly centered near one indicates that price rigidities are likely to be negligible in the market. The various plots in Figure 9 are indicative of a tendency toward an increasing share of intra-hour bid changes. While the movements in the quantiles of the distribution over time are not all pointing in the same direction, overall it seems clear that price rigidities do not seem to have increased through time.[26]

Finally, from these histograms it is also evident that, if one of the objectives of having financial traders into the IPEX day-ahead market was to eliminate rigidities, this goal has unlikely been achieved thus far. Indeed, only 2015 seems to be characterized by a relatively high frequency of plants that perform intra-hour bid changes, while most other years indicate a relatively modest increase in this measure proxy of market efficiency.

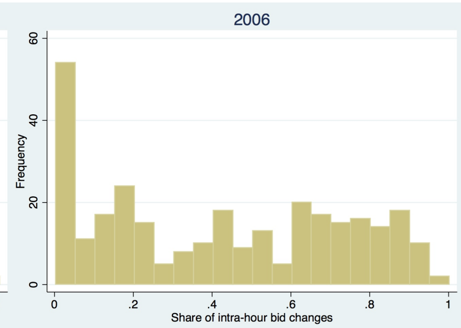
[26] Qualitatively similar results to the ones abstained with this definition were also found with alternative definitions of the variable. For instance, I experimented with looking at changes occurring across consecutive days for the same hour.

Figure 9: Frequency of Bid Changes across Consecutive Hours by the Same Operator

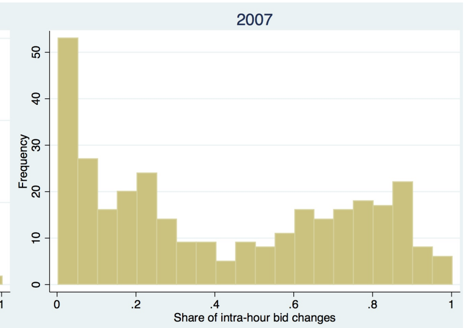
(a)



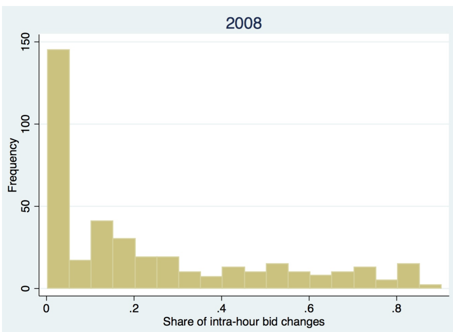
(b)



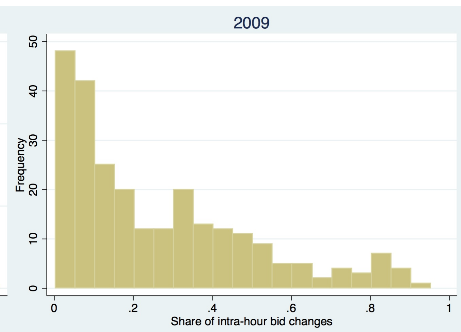
(c)



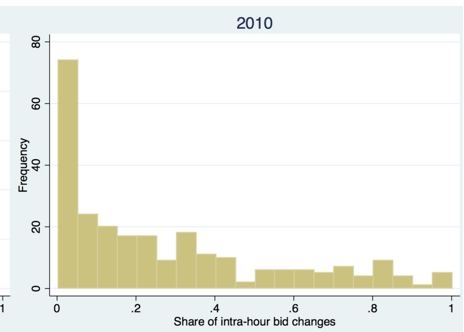
(d) 2011 - Universal



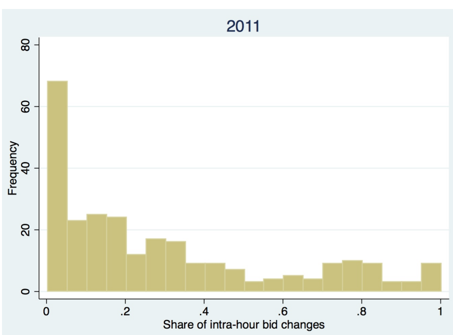
(e)



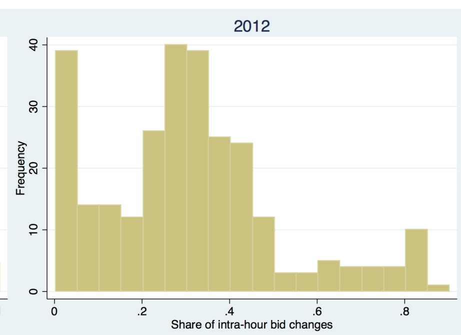
(f)



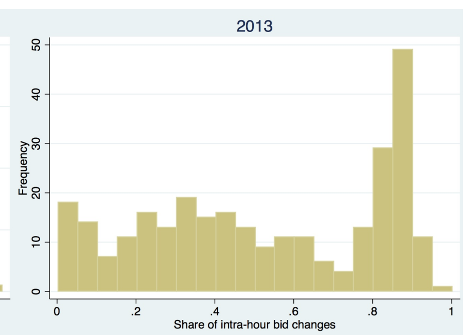
(g)



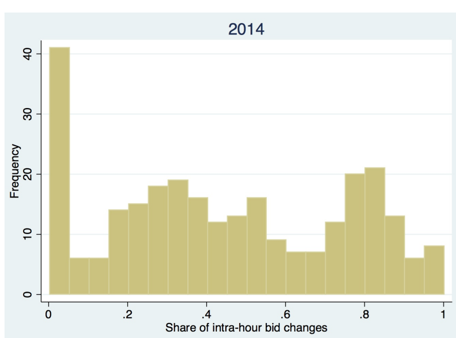
(h)



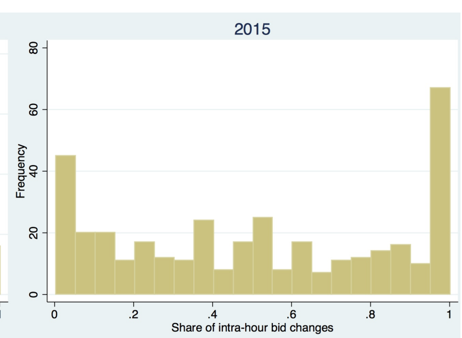
(i)



(j)



(k)



The plots report, separately for each year in the sample, for each bidding plant the share of its bids entailing a price change relative to the following hour of the same day (until 11pm), out of all the plant's bids.

IX.3 Changes in composition of suppliers and in their strategies

The discussion in the previous sections has highlighted a change in the composition of the firms selling electricity on the day-ahead market with a marked increase in the role of financial operators. This subsection empirically explores to what extent this increase can be part of the explanation for the decreased pass-through. Contrary to the lack of relevant changes observed for the measures of market power (number of winners, HHI and collusion) and frictions (intra-hour bid changes), phase III is characterized by a substantially different share of marginal bids placed by virtual operators relative to the other two phases. In particular, as seen in Table 1, while in phase I about 1 percent of the marginal bids is submitted by financial traders, this share increases to 11 percent in phase II and then to 41 percent in phase III.

Phase III therefore appears different from the previous two phases in terms of bidders composition and this fact, in light of the theoretical discussion in section 3, can be a driver of lower pass-through if these financial operators adopt sophisticated trading strategies that exploit the connection between the electricity and ETS markets. A major difficulty in explicitly assessing to what extent financial players are involved in the change of pass-through is that no data is available on their trading positions in the ETS market. Nevertheless, this section will present several pieces of evidence based on both the direct effects of their presence and indirect effects, as implied by the model in section 3. All this evidence will offer a coherent answer, pointing toward the relevant role of financial traders in explaining the lower pass-through.

As a starting point to explore their role, I present in Table 14 simple counts of the number of times that the marginal bid was paced by a financial operator relative to a non-financial operator. The table is organized as follows: in panel (a), the sample is divided into the six geographical areas in which the market is subdivided; in panel (b), the same geographical subdivision is maintained, but limiting the data to phase III; in panel (c), the sample is divided by year. The table reveals several interesting features of the activity of financial operators. First, their presence is rather pervasive across all regions and it increases in phase III. Although the increase in phase III is not symmetric across regions, no geographical area stands out as being unusually exposed to their presence (or the lack of it).

Table 14: Virtual Operators: Number of Marginal Bids by Region and Year

Panel (a): By Geographical Area (All Years)

	(1) NORD	(2) CNOR	(3) CSUD	(4) SUD	(5) SARD	(6) SICI
Virtual Operator=0	86,933	66,542	80,157	69,629	84,397	90,752
Virtual Operator=1	9,440	29,831	16,216	26,744	11,976	5,620

Panel (b): By Geographical Area (Phase III)

	(1) NORD	(2) CNOR	(3) CSUD	(4) SUD	(5) SARD	(6) SICI
Virtual Operator=0	12,529	5,385	10,245	5,415	9,073	14,693
Virtual Operator=1	2,655	10,293	5,867	10,965	7,047	3,709

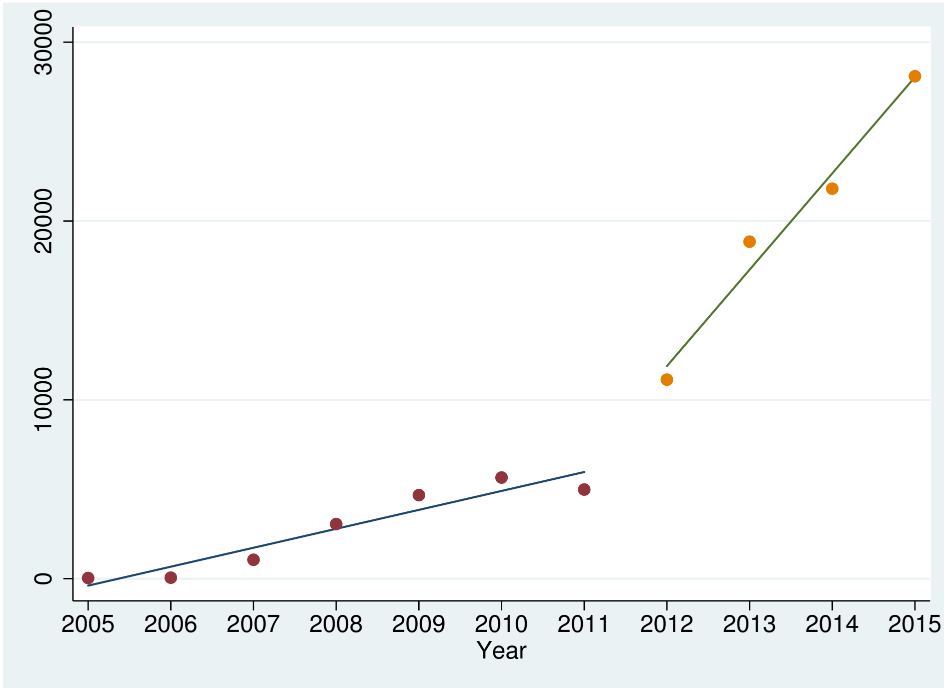
Panel (c): By Year

	(1) 2005	(2) 2006	(3) 2007	(4) 2008	(5) 2009	(6) 2010
Virtual Operator=0	52,518	52,498	51,354	49,194	47,882	46,909
Virtual Operator=1	36	56	1,056	3,504	4,672	5,645

	(7) 2011	(8) 2012	(9) 2013	(10) 2014	(11) 2015
Virtual Operator=0	47,572	41,569	33,710	30,746	24,458
Virtual Operator=1	4,982	11,128	18,844	21,808	28,096

The table reports the number of marginal bids placed by virtual operators (*Virtual Operator*=1) and the other operators (*Virtual Operator*=0). The table is organized as follows: in panel (a), the sample is divided into the six geographical areas in which the market is subdivided; in panel (b), the same geographical subdivision is maintained, but limiting the data to phase III; in panel (c), the sample is divided by year.

Figure 10: Number of Marginal Bids by Virtual Operators



The figure reports the total number of marginal bids originating from bidders that are *financial operators*, separately for each year in the sample.

On the contrary, the sample split by year, panel (c), indicates a clear discontinuity in the role of virtual operators happening in 2012. Before this date, the number of marginal bids placed by virtual operators grows at a fairly low rate so that in 2011 the share of such bids relative to the total number of marginal bids is about 5 percent. In 2012, however, this share doubles relative to 2011 and then keeps on increasing at a very fast rate reaching a stunning 53 percent in 2015.

The rather dramatic change occurring in 2012 is clearly illustrated by Figure 10. In this figure, I report a scatter plot with the same information of panel (c) of Table 14, but also including two regression lines: one for the years from 2005 to 2011 and one for the years 2012 to 2015. The change in both the levels and the growth rate are clear. It is then natural to wonder what drove such transformation in the Italian market. A review of the regulatory changes occurring around 2012 indicates that the most likely explanation is the combined effect of two elements which the 2012 Annual Report of the GME, the company managing electricity exchange, describes as follows:[27]

"The increment (in traded volumes) derives mostly from a change in the behavior of the non

[27] See page 49 of 2012 Annual Report of the GME, released in the summer 2013.

institutional operators and, markedly, of those with a position of net sellers. Several of them have modified their selling strategy, increasing sell bids on volumes originating from bilateral trades and lowering, simultaneously, sell bids pertaining to trades happening on the exchange (i.e., the IPEX). This resulted in an increase in the market liquidity driven by an increase in both the sales and the purchases, as resulting from a greater program unbalancing with negative sign. This behavior might signal the quest for lower financial guarantees to offer to the GME, whereas the credits of the operators matured toward the GME, thanks to the greater volume of sales happening on the exchange, exceed the debts matured by the same operators toward the GME as a consequence of the greater program unbalancing with negative sign."

This first motive is therefore linked to strategies involving the program unbalancing. In order to ensure that the right amount of electricity is available at any time, the producers have to submit "programs" which represent forecasts of how much electricity they will supply. Any difference between the electricity effectively dispatched to the network and that forecasted in the program generates a program unbalancing. Depending on the sign of the unbalancing, this represents a cost or a revenue for the producer. Not all producers, however, are subject to the same requirements in terms of the programs that they have to submit and this can create distortions. Indeed, this aspect is emphasized even more clearly by the other motive listed in the 2012 Annual Report (AEEGSI, 2012) as the source of increase in the traded volumes:

"A contribution to the growth in volumes traded on the exchange might also derive from the revision of the regulation (by the Authority for Electricity and Gas) concerning the dispatch service of electricity by the plants based on renewable and non-programmable sources (see decree 281/2012/R/EFR) aimed at transferring to the producers in this class the cost of the program unbalancing due to their supply."

The consequence of this reform has been that of promoting the role of financial traders that can aggregate the potential supply of the producers of renewables in order to more effectively act on the market, without risking to face high costs of program unbalancing. In principle, it seems indeed reasonable that a trader aggregating multiple producers from different renewable and non-programmable sources can better hedge against possible drops in the electricity dispatched.

Table 15: Electricity Price Pass-through by Year

Panel (b): Full Specification

	(1) Year 2010	(2) Year 2011	(3) Year 2012	(4) Year 2013	(5) Year 2014	(6) Pooled (Phase II & III)
Mg. emissions costs (ρ)	1.20	0.70	-0.72	-1.46*	-2.02**	0.50***
	(0.79)	(0.81)	(0.87)	(0.64)	(0.52)	(0.15)
Observations	30,374	33,152	33,014	32,479	33,073	256,642
R-squared	0.49	0.44	0.36	0.30	0.30	0.37

Note: *** p<0.01, ** p<0.05, * p<0.1. Standard errors clustered by year and geographical market in parenthesis. The dependent variable is *electricity price*, the marginal bid. The main independent variable is *erateeprice*, the product of the EUA price and the plant's emission intensity. The different columns report the IV regression estimated via 2SLS for *erateeprice* on *electricity price*, where the instrument is the EUA price. Panel (a) uses the same specification of column (1) of Table 6, separately for each of the six geographical regions. Panel (b) uses the same specification of column (6) of Table 6, separately for each of the six regions.

Nevertheless, this also increases the market power of these virtual operators. Given their trading activities in the ETS market, this can potentially produce trading strategies capable of sinking the pass-through rate, as revealed by the data. Although no direct evidence on individual trades on the ETS market is observable, the association between the role of virtual operators and the decline in the pass-through is suggested by several pieces of evidence. First and most crucially, the timing of the drop in the pass-through rate is not linked to the implementation of phase III of the ETS but with changes occurring in 2012. This is clearly seen through the estimates reported in Table 15. There I report in the first four columns the estimates of the most parsimonious specification of the baseline estimates (column (1) of Table 6) on four different samples, each containing a single year of data between 2010 and 2014.[28] The coefficient clearly indicate that 2012 is the first year in which the sign of the coefficient flips from being positive to being negative.

The magnitude of this negative coefficients also increases as the sample year grows between 2012 and 2014, from -0.72 to -2.02. Indeed, when I pool together all the years of phase II and III and perform the regression of the same regression specification, while also including a dummy for the year being 2012 or greater, I obtain the positive and statistically significant coefficient of 0.5 reported in the last column of the table. This clearly suggest that accounting for the specificity of what happened starting in 2012. But the change of the composition of bidders on the supply side appears to be the only relevant change that occurred in 2012.

To further corroborate the idea that the spread of financial operators at the end of phase II is the source of the unusual pass-through estimates in phase III, I analyze the pass-through regressions for the individual geographical regions during phase III. As mentioned earlier, no region is unusual in phase III in terms of its relative share of virtual versus non-virtual operators. Therefore, finding that the pass-through estimates at regional level during phase III are systematically in line with those reported in the baseline estimates would confirm that the driver of the pass-through decline resides at national and not regional level. Table 16 confirms this fact by showing the estimates obtained separately for each one of the six regions either with the most parsimonious specification of the baseline estimates (panel (a)) or with the most saturated specification (panel (b)). In all cases, with the exception of the parsimonious specification for the Sardinia market, the estimates

[28]Clearly, relative to column (1) of Table 6 estimating the model with a single year of data requires dropping all the year fixed effects.

are of sign and magnitude incompatible with a positive pass-through.

Finally, the third feature that is suggestive of the relevant role of financial traders and, more specifically, of their sophisticated strategies in the electricity and ETS markets derives from an observable implication of the nuanced model described in Section 3. This implication pertains to the reduction in the variance of the price of the emissions allowances and it is a result from increased presence of financial players in the permit market over time and a decreased presence of production firms over time.

To see why an increase in financial players might reduce the variance in permit prices consider the nuanced model in Section 3 and now suppose there are 2 financial firms with market power in the permit market. If the firms engage in tacit collusion, both buying the same 'directional hedge' and alternating together then outcomes will be similar especially with regards to high price variance. However as the number of financial firms increases this type of strategy breaks down. Specifically, following from the discussion of 'strategy 1' and 'strategy 2' in Section 3, the further the price goes down from strategy 1, the more profitable switching to strategy 2 becomes and vice versa. However if one firm is engaging in strategy 1, short selling permits in an attempt to drive down electricity prices, while another firm is engaging in strategy 2, buying up permits in an attempt to drive up electricity prices, then both firms will take a loss in the permit market and the net effect on price may be no change at all. In such a case, the variation in price will fall and the incentives to engage in either of these strategies will disappear.

Additionally the decreased presence of production firms exacerbates the decline in the profitably of the financial firms across market strategies. As the downstream market becomes more concentrated the pass-through decreases which reduces the ability of financial firms to manipulate electricity prices though exerting market power in the permit market.[29] Indeed, while both the mean and the variance in the emission price decline across the three phases, the drop in the variance is especially marked. Indeed, the coefficient of variation declines from 0.46 in phase II to 0.24 in phase III.[30]

[29]Interestingly, an unintended benefit of the trading of virtual operators is that financial firms, who have neither the intention nor the capacity to generate pollution, hold on to pollution permits and therefore contribute to the reduction in greenhouse gasses.

[30]In phase I, it was 0.82. However, this phase entailed the major market crash described earlier which magnifies the variance observed in this period.

Table 16: Electricity Price Pass-through in Phase III: Regional Differences

Panel (a): Baseline Specification

	(1) NORD	(2) CNOR	(3) CSUD	(4) SUD	(5) SARD	(6) SICI
Mg. emissions costs (ρ)	0.10	-0.64	-0.36	-3.06	1.35*	-0.51
	(1.73)	(1.41)	(0.77)	(2.36)	(0.43)	(0.77)
Observations	15,184	15,678	16,112	16,380	16,120	18,402
R-squared	0.51	0.44	0.50	0.31	0.27	0.59

Panel (b): Full Specification

	(1) NORD	(2) CNOR	(3) CSUD	(4) SUD	(5) SARD	(6) SICI
Mg. emissions costs (ρ)	-0.38	-0.50	-0.55	-1.27	0.93	-1.09**
	(1.46)	(1.12)	(0.97)	(0.46)	(0.95)	(0.18)
Observations	15,154	15,672	16,103	16,365	16,118	18,397
R-squared	0.66	0.63	0.67	0.70	0.75	0.71

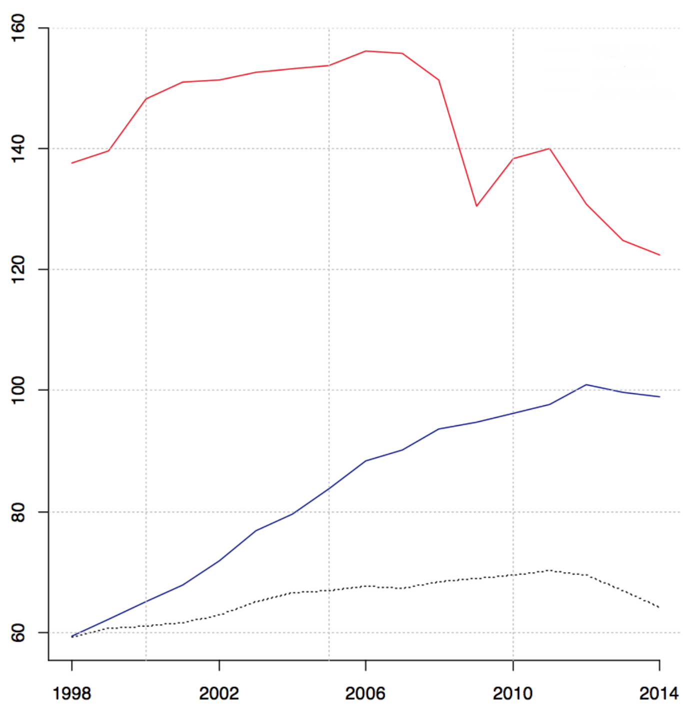
Note: *** p<0.01, ** p<0.05, * p<0.1. Standard errors clustered by year and geographical market in parenthesis. The dependent variable is *electricity price*, the marginal bid. The main independent variable is *erateeprice*, the product of the EUA price and the plant's emission intensity. The different columns report the IV regression estimated via 2SLS for *erateeprice* on *electricity price*, where the instrument is the EUA price. Panel (a) uses the same specification of column (1) of Table 6, separately for each of the six geographical regions. Panel (b) uses the same specification of column (6) of Table 6, separately for each of the six regions.

IX.4 Changes in demand

The last factor that I analyze concerns changes in electricity demand. The evolution of demand in recent years has mirrored the more general decline in the economic situation. Interestingly for my analysis, the beginning of the recent phase of decline in electricity (total) demand started in 2012, which, as seen before, is a crucial year to understand the decline in the pass-through.

More specifically, as shown in Figure 11, the demand from the manufacturing sector had begun declining already in 2011, but it was only in 2012 that also the demand from the service sector and from households started declining too. The decline of -1.9 percent in 2012 relative to 2011 has further increased in 2013 with a drop of -3.0 percent relative to 2012. Only in 2015 this trend has been reversed with an increase of 1.5 percent relative to 2014.

Figure 11: Electricity Demand



The figure shows the evolution of Italian electricity demand (in billion of kWh) over time: the dotted line represents household demand; the solid lines represent demand from the business sector with the manufacturing sector in red and the service sector in blue. Source: Elaborations from Terna data.

The long term view offered by Figure 11 illustrates the peculiar circumstances that occurred in 2012, with the first ever decline in household electricity demand since the beginning of the series in 1998. This situation might have plausibly triggered changes in the market leading to a change in the pass-through rate. In particular, recalling the discussion in Section 3, a declining pass-through could emerge as the result of a decrease in demand elasticity. Therefore, I begin the analysis of the demand drivers of pass-through changes from an assessment of how the price elasticity of demand evolved across the three phases of the ETS.

The data released by the IPEX contains all the demand bids placed in the day-ahead market. Thus, the structure of the data is such that in theory we could estimate demand elasticity for each hour of the day for each day between the beginning of 2005 and the end of 2015. However, the number of auctions per hour is not sufficient to render such analysis feasible. Trading off precision and accuracy, I estimate demand elasticity separately for each zone in every month for both peak and no-peak hours. I do so to account for spatial and temporal variation in electricity demand. This specification leaves me with a little over 1600 markets, m, each with no less then 270 observations, i, per market.

The elasticities are calculated through a log-log regression. For each of the prices observed in a market, I regress the log of the total quantity demanded, $\tilde{q}_{im}$, at prices greater than or equal to the observed price, on the the log price, p_{im}. That is:

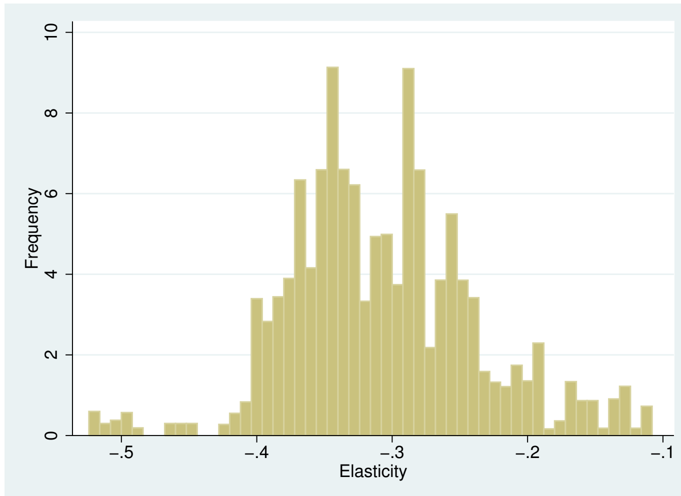
$$\ln(\tilde{q}_{im}) = \eta_m \ln(p_{im}) + u_{im}, \tag{7}$$

where $\tilde{q}_{im} = \sum q_{jm}$ s.t. $p_{jm} \geq p_{im}$ and η is the elasticity parameter that I seek to estimate.

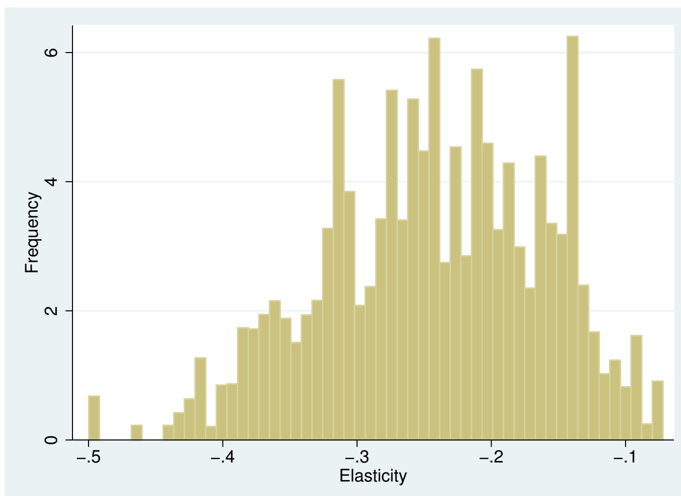
As such, the elasticities are derived from market specific aggregate demand schedules. It is important to note that auctions where a transaction did not occur are included to trace out the portion of the demand curve below the observed willingness to sell. I find substantial heterogeneity between peak and non-peak hours, and over time. For comparison, I also estimate time invariant elasticity for each zone and indeed time variation is important, for example demand is generally more elastic outside of peak hours. While these estimates are informative, and indeed Figure 12 shows that they are quite reasonable, they should be interpret with caution as no instrument for quantity was used and thus bias from contemporary shocks influencing supply and demand may be present.

Figure 12: Price Demand Elasticity

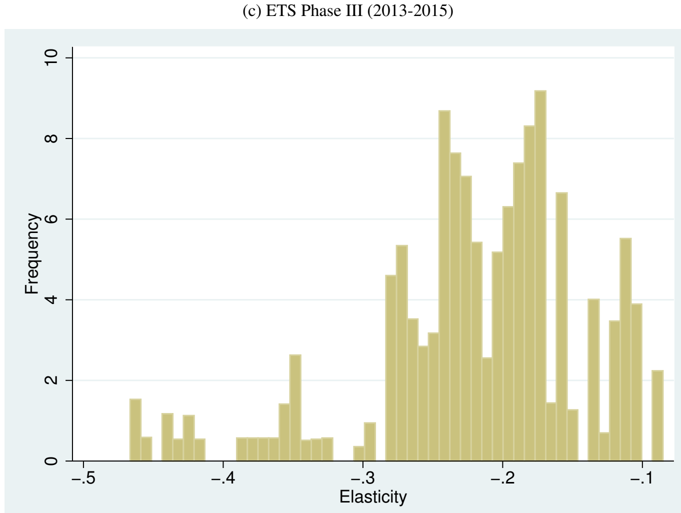
(a) ETS Phase I (2005-2007)



(b) ETS Phase II (2008-2012)



(c) ETS Phase III (2013-2015)



The three plots report the elasticity estimates obtained for the three sub-periods analyzed.

The estimates obtained indicate a decline in electricity across the three phases. The average elasticity estimated for phase I is -0.31 (standard deviation 0.07), it declines to -0.24 (0.08) in phase II, and then it declines further to -0.23 (0.10).[31] While the direction of the elasticity change is compatible with a reduced pass-through, the specific dynamic of the elasticity seems better able to explain the drop in the pass-through observed between phase I and II, then the one between phase II and III. Indeed, while the drop in elasticity between the first two phases is substantial, the one one between the following two phases is negligible. Moreover, the changes in demand are somewhat gradual and unable to explain the sharp change that occurred in 2012.

To further corroborate the above discussion, Table 17 reports the baseline estimates of Table 6, but including the estimated elasticity, η, from equation (7) as an additional control. While using an estimated parameter as a covariate might produce problems related to the inference on the coefficient of such variable (due to the proper calculation of the standard errors), my interest is exclusively on how this richer specification affects the pass-through coefficient, ρ.

What the estimates in Table 17 reveal is rather interesting and it is consistent with the above discussion of the effects of the elasticity on the change in phase II. First, by comparing the estimates in Table 17 to those in Table 6, I find that the inclusion of the elasticity control tends to reduce the magnitude of the pass-through coefficient and increase the precision of its estimate. While the change in magnitude is small enough not to make the difference in the coefficients statistically significant, it amounts roughly to a 3 percent change in the estimate which is economically interesting.

Second, the reduction in the pass-through coefficient relative to the baseline estimates tends to be more pronounced in phase II than in phase I. Indeed, the estimates inclusive of the elasticity term magnify the difference between the phase I and phase II estimates. For instance, for the least saturated specification (model (1)), the differences between the phase I and II estimates passes from 0.22 in the baseline estimates to .36, which amounts to about twice the value of those coefficients' standard deviation. This difference, however, becomes more contained for the more saturated model specifications.

[31] As discussed in Section 2, these estimates are remarkably close to those reported in the meta analysis of Labadeira et al. (2017) which indicates an average (short run) elasticity of -0.21.

Third, the inclusion of the elasticity does not have any role in solving the question of why the phase III estimates are problematic for the pass-through estimates, which are all not statistically significant. Altogether, the evidence is therefore suggestive that changes in the elasticity of demand, while important to understand the reduction in the pass-through estimates from phase I to II, do not seem relevant to explain the lack of any positive pass-through in phase III.

Table 17: Electricity Price Pass-through Estimates: Demand Elasticity

Panel (a): ETS Phase I (2005-2007)

	(1)	(2)	(3)	(4)	(5)	(6)
Mg. emissions costs (ρ)	0.78***	0.76***	0.75***	0.68***	0.66***	0.66***
	(0.16)	(0.09)	(0.09)	(0.08)	(0.04)	(0.04)
Observations	99,734	99,734	99,734	99,706	99,706	99,706
R-squared	0.56	0.70	0.70	0.68	0.78	0.78
Input price (coal, gas, oil)	Yes	Yes	Yes	Yes	Yes	Yes
Time FE (yr, mo, dy, hr)	Yes	Yes	Yes	Yes	Yes	Yes
Demand controls	No	Yes	Yes	No	Yes	Yes
Supply controls	No	No	Yes	No	No	Yes
Plant FE	No	No	No	Yes	Yes	Yes

Panel (b): ETS Phase II (2008-2012)

	(1)	(2)	(3)	(4)	(5)	(6)
Mg. emissions costs (ρ)	0.42***	0.41***	0.41***	0.29***	0.28***	0.28***
	(0.12)	(0.12)	(0.12)	(0.10)	(0.08)	(0.08)
Observations	158,766	158,766	158,766	158,728	158,728	158,728
R-squared	0.43	0.60	0.60	0.67	0.73	0.73
Input price (coal, gas, oil)	Yes	Yes	Yes	Yes	Yes	Yes
Time FE (yr, mo, dy, hr)	Yes	Yes	Yes	Yes	Yes	Yes
Demand controls	No	Yes	Yes	No	Yes	Yes
Supply controls	No	No	Yes	No	No	Yes
Plant FE	No	No	No	Yes	Yes	Yes

Panel (c): ETS Phase III (2013-2015)

	(1)	(2)	(3)	(4)	(5)	(6)
Mg. emissions costs (ρ)	-0.61	-0.68	-0.75	0.47	0.40	-0.47
	(0.41)	(0.43)	(0.45)	(0.32)	(0.31)	(0.37)
Observations	97,876	97,876	97,876	97,809	97,809	97,809
R-squared	0.24	0.51	0.52	0.65	0.71	0.71
Input price (coal, gas, oil)	Yes	Yes	Yes	Yes	Yes	Yes
Time FE (yr, mo, dy, hr)	Yes	Yes	Yes	Yes	Yes	Yes
Demand controls	No	Yes	Yes	No	Yes	Yes
Supply controls	No	No	Yes	No	No	Yes
Plant FE	No	No	No	Yes	Yes	Yes

Note: *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Standard errors clustered by year and geographical market in parenthesis. The dependent variable is *electricity price*, the marginal bid. The main independent variable is *erateeprice*, the product of the EUA price and the plant's emission intensity. The different columns report the IV regression estimated via 2SLS for *erateeprice* on *electricity price*, where the instrument is the EUA price. The structure of the table is identical to that of the baseline estimates (Table 6) with the only difference that each model specification (1)-(6) is augmented with one control: the price demand elasticity as calculated in the way described in the text.

As a final check on the role played by demand factors, I consider whether changes in the composition of demand might be a relevant driver of the changes in the pass-through. As seen for the supply side, it was not market power by itself, but the shift in the composition of suppliers from traditional electricity generators toward financial operators that played a key role to understand the dynamic of the pass-through. Following a similar approach, I explore next how the baseline estimates are modified by introduction of a series of controls for the type of buyers.

Here I exploit the variables constructed from the demand bid data that I described at the end of the Section V and that capture the share of demand arising from the Single Buyer and the virtual operators, respectively. Relative to the baseline estimates, Table 18 includes additional controls for demand features as follows: columns (1) and (2) include the share of electricity demanded by the Single Buyer over total demand; columns (3) and (4) include the monthly-average of the share of electricity demanded by the Single Buyer over total demand; columns (5) and (6) include the share of electricity demanded by virtual operators over total demand, where virtual operators are the same set of firms that where categorized as virtual operators when looking at the supply bids.

The estimates in Table 18 indicate that, contrary to the case of the demand elasticity, the composition of demand by itself does not influence the estimated pass-through. Both the estimated coefficients as well as their standard errors remain essentially identical to those in the baseline estimates. Among the demand-type controls included, the one measuring the share of demand from the Single Buyer is, in relative terms, the one that affects the most the value of the pass-through estimates, but never inducing a coefficient estimate that is statistically different from that of the baseline estimates.

Furthermore and most crucially, these new specifications do not help addressing the non-positive pass-through estimated for phase III. Clearly, the increase in the demand by virtual operators, which parallels their increase on the supply side, matters for the pass-through estimates, but in a way that my estimates are able to capture exclusively as a difference between the pre and post expansion of virtual operators that occurred in 2012 (as seen in Table 15).

As shown in Table 2, even in phase III the role of financial operators on the buying side remains, however, substantially more limited than that on the supply side, never exceeding 10 percent of the total demand. Compared to the nearly 50 share of marginal bids placed, this indicates that financial operators while accounting for a modest, but non trivial, portion of demand have a crucial role in the price setting mechanism determining the price at which this demand will be served.

Therefore, I conclude that demand factors, and in particular the decline in price demand elasticity, are likely relevant to explain the drop in the pass-through between phase I and II, but are not directly responsible for the further decline in phase III, if not for the fact that virtual operates in this market affect both the supply and the demand.

Table 18: Electricity Price Pass-through Estimates: Demand Composition

Panel (a): ETS Phase I (2005-2007)

	(1)	(2)	(3)	(4)	(5)	(6)
Mg. emissions costs (ρ)	0.75***	0.62***	0.75***	0.63***	0.73***	0.65***
	(0.15)	(0.03)	(0.15)	(0.03)	(0.16)	(0.03)
Observations	99,734	99,706	99,734	99,706	99,734	99,706
R-squared	0.57	0.78	0.57	0.78	0.57	0.78
Single Buyer	Yes	Yes	No	No	No	No
Single Buyer (Avg.)	No	No	Yes	Yes	No	No
Virtual Operators	No	No	No	No	Yes	Yes
Plant FE	No	Yes	No	Yes	No	Yes

Panel (b): ETS Phase II (2008-2012)

	(1)	(2)	(3)	(4)	(5)	(6)
Mg. emissions costs (ρ)	0.54***	0.33***	0.54***	0.32***	0.54***	0.32***
	(0.14)	(0.10)	(0.14)	(0.10)	(0.15)	(0.10)
Observations	158,766	158,728	158,766	158,728	158,766	158,728
R-squared	0.43	0.73	0.43	0.73	0.43	0.73
Single Buyer	Yes	Yes	No	No	No	No
Single Buyer (Avg.)	No	No	Yes	Yes	No	No
Virtual Operators	No	No	No	No	Yes	Yes
Plant FE	No	Yes	No	Yes	No	Yes

Panel (c): ETS Phase III (2013-2015)

	(1)	(2)	(3)	(4)	(5)	(6)
Mg. emissions costs (ρ)	-0.56	-0.44	-0.57	-0.34	-0.29	-0.51
	(0.42)	(0.36)	(0.42)	(0.35)	(0.56)	(0.37)
Observations	97,876	97,809	97,876	97,809	97,876	97,809
R-squared	0.24	0.71	0.23	0.71	0.28	0.71
Single Buyer	Yes	Yes	No	No	No	No
Single Buyer (Avg.)	No	No	Yes	Yes	No	No
Virtual Operators	No	No	No	No	Yes	Yes
Plant FE	No	Yes	No	Yes	No	Yes

Note: *** p<0.01, ** p<0.05, * p<0.1. Standard errors clustered by year and geographical market in parenthesis. The dependent variable is *electricity price*, the marginal bid. The main independent variable is *erateeprice*, the product of the EUA price and the plant's emission intensity. The different columns report the IV regression estimated via 2SLS for *erateeprice* on *electricity price*, where the instrument is the EUA price. The model specification changes across columns. All specifications include controls for the price of coal, gas and price, all multiplied for a dummy for whether the technology of the plant involves consuming such input. Always included are also fixed effects for the year, month, day and hour. Even numbered columns include suppliers' fixed effects. Additional controls for demand features are included as follows: columns (1) and (2) include the share of electricity demanded by the Single Buyer over total demand; columns (3) and (4) include the monthly-average of the share of electricity demanded by the Single Buyer over total demand; columns (5) and (6) include the share of electricity demanded by virtual operators over total demand.

X Conclusions

This study has analyzed the pass-through of the CO2 emissions' price under the European ETS to the wholesale electricity price in Italy. Exploiting a detailed dataset containing all the plant-level bids in the the Italian day-ahead electricity auctions held between the beginning of 2005 and the end of 2015, I implemented an instrumental variable strategy allowing me to obtain a clean identification of the pass-through rate. There are three main findings in the paper. First, throughout the whole sample period analyzed the degree of pass-through is below the value of one that should characterize a competitive market. Second, the estimated pass-through steadily declines over time across the three regulatory phases of the ETS covered in the sample: from an estimate of about 70 percent during phase I (2005-2007), to an estimate of about 30 percent during phase II (2008-2012) and finally to an estimate undistinguishable from zero in phase III (2013-2015). Third, a change in the composition of suppliers away from traditional electricity generators and toward purely financial intermediaries appears to be the key driver of the decline of the pass-through observed in the most recent years. More specifically, by exploiting the different timing with which demand and supply features of the market evolved, I find that the decline in the pass-through in the latest phase of the ETS is associated with a sudden increase in both the level and the growth rate of the share of marginal (i.e, price setting) bids placed by financial traders. In the same way, I also argue that a reduction in the price elasticity of demand is likely to have been an important determinant of the decline observed for the second phase of the ETS, but not for that occurred in its third phase.

These results complement the rapidly growing literature on the pass-through of environmental policies on energy and electricity prices. Most notably, they present evidence consistent with that in the study of Fabra and Reguant (2014) about the Spanish electricity market during the first phase of the ETS. However, they also expand on their findings by showing interesting dynamics of the pass-through rate in the next two regulatory phases. The evidence on the role played in this decline by financial operators complements a series of recent studies (most notably Mercadal, 2016, and Birge, Hortacsu and Mercadal, 2016) that, using data from US electricity markets, are showing the presence of both intended and unintended consequences of the expanded role of financial operators in the electricity markets.

In the case of the Italian electricity market that I analyze, the evidence that an expanded role of financial traders is associated with the loss of any pass-through rate of the ETS on electricity price is troubling for at least two reasons. First, the lack of any pass-through despite a low, but not negligible price of emissions allowances might imply that the ETS is currently unable to correctly steer the incentives of the electricity producers toward the stated environmental goals of the ETS. Second, the sophisticated strategies adopted by financial players that might be behind the zero pass-through result might entail distortions that go beyond the effects related to the ETS and, more broadly, affect the proper functioning of the electricity and pollution permits markets.

These results are therefore important to suggest future avenues of research. First of all, a better understanding of the complex roles played by financial traders would be extremely relevant. A key element needed to achieve this goal, however, would be the availability of data recording their transactions across different but interlinked markets. This seems relevant not only from a research perspective, but also from a policy perspective as ongoing changes in the regulations are facilitating their access to electricity markets in several countries, including Italy and the US. In Italy, for instance, the growing limits placed by the regulator to the generators using renewable and non-predictable sources are likely inducing a greater integration between these producers and financial traders. Therefore, it would be crucial for the regulator to ensure that the appropriate data are recorded and analyzed so that the full set of implications of this type of reform is properly assessed.

As suggested by the discussion above relating Italy and the US, the phenomena analyzed in this paper are likely happening in similar ways across multiple countries. This is most obviously true for the countries within the European Union which are subject to broadly the same regulations both in terms of electricity and pollution permit markets. Therefore, a second fruitful avenue of potential research would be to repeat the analysis conducted in this paper to also include other European states. The comparability of my estimates with those of Fabra and Reguant (2014) for Spain and Hinterman (2014) for Germany for the subset of periods on which there is overlap, is highly suggestive that this approach is both feasible and likely useful to gain a deeper understanding of the complex interactions governing the relationship between the ETS and electricity prices.

A third area toward which my results could be extended regards a better integration within the pass-through analysis of the broader set of environmental policies affecting the electricity prices in Europe. Although this study has focused on the ETS due to its prominent role as the main tool through which the EU is seeking to achieve its goals under the Kyoto Protocol and due to the sheer size of this market, a plethora of other environmental policies exist and some might be particularly relevant to achieve an accurate assessment of how environmental policies affect electricity prices.

The ultimate reason why gaining a full understanding of the pass-through of environmental policies on electricity prices matters is the key role that electricity prices play on household and firms' choices. Although this paper has mostly focused on the behavior of electricity suppliers, the demand side of electricity plays a crucial role. First, as also my analysis has shown, demand features feed back to supplier's choices and through them contribute to determine the pass-through. Second and more generally, demand from household and firms is essential to quantify the overall welfare implications of any environmental policy. Thus, it is relevant to point out that the demand analysis based on individual-level demand bids performed in this paper, albeit simple and limited in scope to the question of the pass-through assessment, could be a valuable starting point for a more in depth demand estimation analysis aimed at performing a broader welfare evaluation of the ETS program. In the spirit of Labandeira et al. (2017), this should ideally involve understanding both short run and long run demand behaviors and is a task that I leave for future research.

XI References

Abrantes-Metz, R., P. Bajari, (2012). “Screens for Conspiracies and Their Multiple Applications,” *Competition Policy International Journal*, 8 (1) 177-83.

Aguirre, I., S. Cowan, J. Vickers, (2010). “Monopoly Price Discrimination and Demand Curvature,” *American Economic Review* 100 (4): 1601-15.

AEEGSI, (2006). *Relazione Annuale sullo Stato dei Servizi e sull’Attività Svolta*, Autorità per l’Energia Elettrica il Gas e il Sistema Idrico, Rome, Italy.

AEEGSI, (2012). *Relazione Annuale sullo Stato dei Servizi e sull’Attività Svolta*, Autorità per l’Energia Elettrica il Gas e il Sistema Idrico, Rome, Italy.

AEEGSI, (2016). *Relazione Annuale sullo Stato dei Servizi e sull’Attività Svolta*, Autorità per l’Energia Elettrica il Gas e il Sistema Idrico, Rome, Italy.

Bel, J., S. Joseph, (2015). “Emission abatement: Untangling the impacts of the EU ETS and the economic crisis,” *Energy Economics* , 49, 531-539

Bessembinder, H., M. L Lemmon, (2002). “Equilibrium pricing and optimal hedging in electricity forward markets, *the Journal of Finance*, 57(3):1347-1382.

Birge, J., A. Hortacsu, I. Mercadal, (2016). “Limits to arbitrage in electricity markets,” mimeo.

Borenstein, S., J. Bushnell, (1999). “An empirical analysis of the potential for market power in California’s electricity industry,” *The Journal of Industrial Economics*, 47(3): 285323, .

Borenstein, S., J. Bushnell, S. Stoft, (1997). “The competitive effects of transmission capacity in a deregulated electricity industry,” Technical report, National Bureau of Economic Research.

Borenstein, S., J. Bushnell, F. Wolak, (2000). “Diagnosing market power in California’s restructured wholesale electricity market,” Technical report, National Bureau of Economic Research.

Borenstein, S., J. Bushnell, C. R Knittel, C. Wolfram (2008). “Inefficiencies and market power in financial arbitrage: a study of California’s electricity markets,” *The Journal of Industrial Economics*, 56(2):347-378.

Bunn, D. W., C. Fezzi (2007). "Interaction of European Carbon Trading and Energy Prices," *Fondazione Eni Enrico Mattei Working Papers*, no. 63-2007.

Chester, L., S. Rosewarne, (2016). "What is the relationship between derivative markets and carbon prices?," mimeo.

Costantini V., A. D'Amato, C. Martini, C. Tommasino, E. Valentini, M. Zoli, (2013). "Taxing International Emissions Trading, *Energy Economics*, 40, 609-621.

DAmato A., E. Valentini, M. Zoli, (2017). "Tradable Quota Taxation and Market Power," *Energy Economics*, 63, 248-252.

Ellerman, D., M. Reguant, (2008). "Grandfathering and the endowment effect: An Assessment in the context of the Spanish National Allocation Plan," MIT-CEEPR W.P. 08-018.

Ellerman, D., B. Buchner, (2006). "Over-Allocation or Abatement. A Preliminary Analysis of the EU ETS Based on the 2005 Emission Data," Fondazione Eni Enrico Mattei working paper 139.2006.

EC, (2015). *ETS Handbook*, European Commission, Bruxelles, Belgium.

Fabra, N., M. Reguant, (2014). "Pass-Through of Emissions Costs in Electricity Markets," *American Economic Review*, 104(9): 2872-2899.

Flues, F., A. Thomas, (2015). "The distributional effects of energy taxes," OECD Taxation Working Papers, N. 23.

GME, (2011). *Vademecum Borsa Elettrica*, Gestore Mercato Elettrico, Rome, Italy.

GME, (2016). *Relazione Annuale*, Gestore Mercato Elettrico, Rome, Italy.

Goldberg, P. K., R. Hellerstein, (2008). "A Structural Approach to Explaining Incomplete Exchange-Rate Pass-Through and Pricing-to-Market," *American Economic Review*. 98 (2): 423-9.

Hardin, G., (1968). "The Tragedy of the Commons," *Science*, vol. 162 (3859).

Hintermann, B., (2017). "Market Power in Emission Permit Markets: Theory and Evidence from the EU ETS," *Environmental Resource Economics*, 66, 89-112

Hintermann, B., S. Petersond, W. Rickels, (2014). “Price and Market Behavior in Phase II of the EU ETS,” Kiel Institute for the World Economy No. 1962.

Harrison, D., S. Sorrell, D. Radov, P. Klevnas, A. Foss, (2005). Interactions of the EU ETS with Green And White Certificate Schemes, NERA final report for DG Environment.

Honkatukia, J., V. Malkonen, A. Perrels, (2006). Impacts of the European emission trade system on Finnish wholesale electricity prices, Government Institute for Economic Research Helsinki working paper.

Hortacsu, A., F. Luco, S. Puller, D. Zhu, (2017). “Does Strategic Ability Affect Efficiency? Evidence from Electricity Markets,” mimeo.

Khan, H., C. Knittel, K. Metaxoglou, M. Papineau, (2015). “Do Carbon Emissions Respond to Business-cycle Shocks?,” mimeo.

Koch, N., S. Fuss, G. Grosjean, O. Edenhofer, (2014). “Causes of the EU ETS price drop: recession, CDM, renewable policies or a bit of everything? - New evidence,” mimeo.

Ito, K., M. Reguant, (2016). “Sequential markets, market power, and arbitrage,” *American Economic Review*.

Jaffe, S., E. G. Weyl, (2013). “The First-Order Approach to Merger Analysis,” *American Economic Journal: Microeconomics* 5 (4): 188-218.

Joskow, P. L., R. Schmalensee, E. M. Bailey, (1998). The Market for Sulfur Dioxide Emissions, The American Economic Review, Vol. 88, No. 4., pp. 669-685.

Joskow, P. L., J. Tirole, (2000). “Transmission rights and market power on electric power networks,” *The Rand Journal of Economics*, pages 450-487.

Labandeira, X., J. M. Labeaga, M. Rodriguez, (2008). “The Costs of Kyoto Adjustments for Spanish Households,” FEDEA WP 2008-02.

Labandeira, X., J. M. Labeaga, X. Lopez-Otero, (2012). “Estimation of elasticity price of electricity with incomplete information,” *Energy Economics*, 34, 3, 627-633.

Labandeira, X., J. M. Labeaga, X. Lopez-Otero, (2017). “A meta-analysis on the price elasticity of energy demand," RSCAS WP 2016-25.

Laing,T., M. Sato, M. Grubb, C. Comberti, (2014). "The effects and side-effects of the EU emissions trading scheme," WIREs Clim Change, 5, pages 509-519

Ledgerwood, S.D., J.P. Pfeifenberger, (2012). "Using virtual bids to manipulate the value of financial transmission rights," mimeo.

Longstaff, F.A., A. W. Wang, (1990). "Electricity forward prices: a high-frequency empirical analysis," *The Journal of Finance*, 59(4):1877-1900.

MacKay, A., N. H. Miller, M. Remer, G. Sheu, (2014). "Bias in reduced-form estimates of pass-through," *Economics Letters* 123, 200-202.

Marion, J., E. Muehlegger, (2011). "Fuel Tax Incidence and Supply Conditions," *Journal of Public Economics* 95 (910): 1202-12.

Mercadal, I., (2016). "Dynamic competition and arbitrage in electricity markets: The role of financial players," mimeo.

Nakamura, E., D. Zerom, (2010). "Accounting for Incomplete Pass-Through," *Review of Economic Studies* 77 (3): 1192-230.

Neuoff, K., K. Martnez, M. Sato, (2006).Allocation, incentives and distortions: the impact of EU ETS emissions allowance allocations to the electricity sector, Climate Policy, 6, pp. 73-91.

Peltzman, S., (2000). "Prices Rise Faster Than They Fall," *Journal of Political Economy,* Vol. 108 (2000), pp. 466-502.

Petrick, S., U. J. Wagner, (2014). "The Impact of Carbon Trading on Industry: Evidence from German Manufacturing Firms," mimeo.

Porter, R., D. Zona, (1993). "Detection of Bid Rigging in Procurement Auctions.," *Journal of Political Economy*, 101 (3): 518-38.

Reinaud, J., (2007). "CO2 allowance and electricity price interaction 2007. Impact on industrys electricity purchasing strategies in Europe," *International Energy Agency Information Paper*.

Schmalensee, R., P. L. Joskow, A. D. Ellerman, J. P. Montero, E. M. Bailey, (1998). "An

Interim Evaluation of Sulfur Dioxide Emissions Trading," Journal of Economic Perspectives, Vol. 12, No. 3., pp. 53-68

Sijm, J.P.M., S.J.A. Bakker, Y. Chen, H.W. Harmsen, W. Lise, (2005). "CO2 price dynamics: The implications of EU emissions trading for the price of electricity," Energy research center of the Netherlands report ECN-C-05-081.

Sijm, J.P.M., Y. Chen, M. Donkelaar, J.S. Hers, M.J.J. Scheepers, (2006). "CO2 price dynamics: A follow up analysis of emissions trading for the price of electricity," Energy Research Center of the Netherlands report ECN-C-06-015.

Sijm, J.P.M., K. Neuoff, Y. Chen, (2006). "CO2 Cost Pass-Through and Windfall Profits in the Power Sector," *Climate Policy*, 6, pp. 49-72.

Tappata, M., (2009). "Rockets and feathers: Understanding asymmetric pricing," *RAND Journal of Economics*, Vol. 40, No. 4, pp. 673-687.

Venditti, F., (2010). "Down the Non-linear Road from Oil to Consumer Energy Prices: No Much Asymmetry Along the Way," *Banca d'Italia - Temi di Discussione*, no. 751.

Verboven, F., T. van Dijk, (2009). "Cartel Damages Claims and the Passing-On Defense," *Journal of Industrial Economics* 57 (3): 457-91.

Wolak, F.A., (2003). "Measuring unilateral market power in wholesale electricity markets: the California market, 1998-2000," *American Economic Review*, pages 425-430.

Wolak, F.A., (2011). "Measuring the benefits of greater spatial granularity in short-term pricing in wholesale electricity markets," *American Economic Review*, 101(3):247, 2011.

Wolfram, C.D., (1999). "Measuring duopoly power in the british electricity spot market," *American Economic Review*, pages 805-826.