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Doctoral Thesis

Essays on the Effect of Renewable Energy Production in the Spanish Electricity Market

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"It is not the mountain we conquer, but ourselves."

Sir Edmund Hillary

Abstract

Moving towards a low carbon economy is currently one of the political priorities of the European Union and regulation has thus been designed to achieve a 20% renewables target by 2020. In Spain, Renewable Energy emerged after the introduction of the Feed-in Tariffs scheme, which caused the penetration of green sources into the electricity market to rise by 69% from 2008 to 2013. As a result, electricity market prices decreased and the market became less concentrated. However, the cost of the regulatory system imposed a great financial burden on consumers. The question from an economic perspective is threefold. First, is Renewable Energy in Spain worth the cost? Second, could this cost have been lower with a different incentive scheme? Third, has Renewable Energy affected other producers' strategies in the electricity market? These questions are relevant because the environmental and socio-economic benefits of renewable production have to be compared to their economic costs in order to determine the optimal level of public support that these technologies should receive.

Additionally, large penetration of intermittent renewable sources (i.e. wind and solar) brings up some efficiency problems, since the electricity system is underused in hours when Renewable Energy is produced at its maximum levels. Hence, another issue needed to be addressed is: would consumers react to price signals and adapt their consumption pattern more efficiently?

Accordingly, the present research anwers to these questions with an analysis of the effect of Renewable Energy in the Spanish electricity market during the period 2008-2013. Both supply and demand sides of the market are explored by means of a methodology which combines economic theory with data analysis and simulation methods.

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Abbreviations

AMP	**A**ctual **M**arket **P**rice
AS	**A**ctual **S**upply
BIO	**BIO**mass/Wastes
CCGT	**C**ombined **C**ycle **G**as **T**urbine **P**lants
CDF	**C**umulative **D**istribution **F**unction
CC	**C**ombined **C**ycle
COG	**COG**eneration
CMP	**C**ounterfactual **M**arket **P**rice
CNE	**C**omisión **N**acional de la **E**nergía (National Energy Commission)
CNMC	**C**omisión **N**acional de los **M**ercados y la **C**ompetencia (National Energy Commission)
CPP	**C**ritical **P**eak **P**rincing
CPR	**C**ritical **P**eak **R**ebate
CS	**C**ounterfactual **S**upply
CT	**C**oal plants
DSM	**D**emand **S**ide **M**anagement
ETS	**E**mission-**T**rading **S**chemes
FIT	**F**eed-**I**n **T**ariffs
FIP	**F**eed-**I**n **P**remiums
HY	**HY**dropower plants
IBR	**I**nclining **B**lock **R**ates
LRT	**L**ast **R**esort **T**ariff
MC	**M**arginal **C**ost
NU	**NU**clear plants
OLS	**O**rdinary **L**east **S**quares
OMIE	**O**perador del **M**ercado **I**bérico de **E**lectricidad

OR	**O**rdinary **R**egime
PHV	Solar **PH**oto**V**oltaic
PPA	**P**ower **P**urchase **A**greement
RE	**R**enewable **E**nergy
REE	**R**ed **E**léctrica de **E**spaña
RES	**R**newable **E**nergy **S**ources
RES-E	**Electricity** from **R**enewable **E**nergy **S**ources
RPS	**R**enewable **P**ortfolio **S**tandards
RTP	**R**eal **T**ime **P**rincing
SHY	**S**mall **H**ydropower
SMP	**S**ystem **M**arginal **P**rice
SR	**S**pecial **R**egime
ToU	**T**ime of **U**se
TGC	**T**radable **G**reen **C**ertificates
TH	Solar **TH**ermal
W	**W**ind power

To my family

Chapter 1

Introduction

1.0.1 Motivation of the thesis

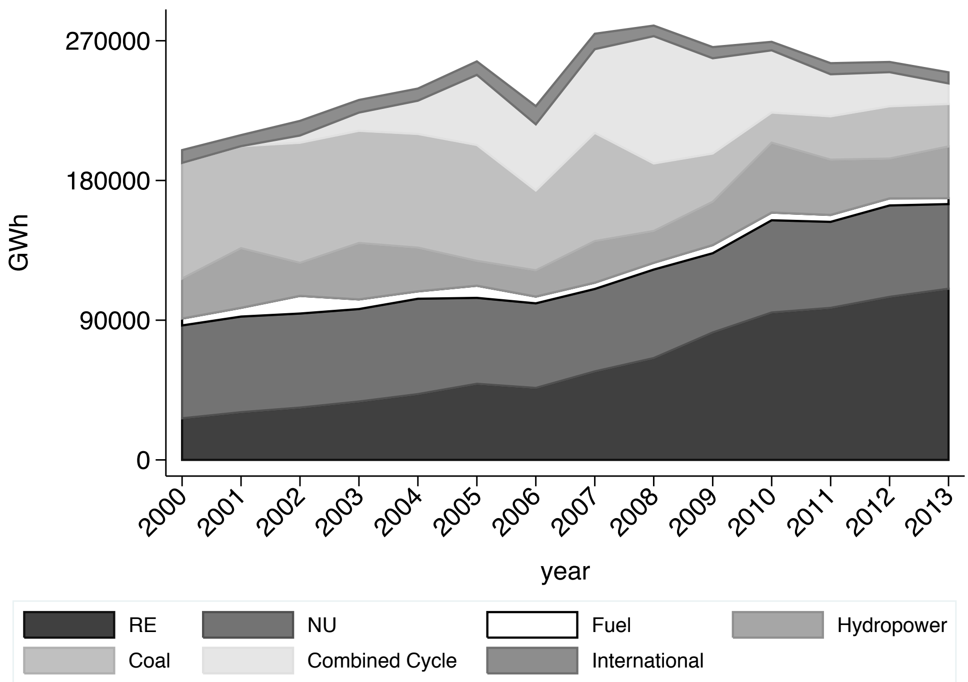
The three pillars of the European Union's energy policy are efficiency, sustainability and security of supply (COM, 2008). In the electricity sector, this trilemma ensures environmental quality, security of supply and economic sustainability simultaneously. In this sense, Renewable Energy (RE) plays a major role, since the use of non-depletable resources not only provides eco-friendly and sustainable electricity production but also mitigates the security of supply issues, since it reduces the dependence on imports of fuel to generate electricity and provides a large number of different technologies.

RE is the energy that is derived from natural processes that are replenished at a higher rate than they are consumed. A source of energy can be called renewable when it cannot run out or can easily be replaced, when it is carbon neutral and when it does not pollute the environment. Therefore, RE includes Biomass, Wind, Solar, Hydropower, Geothermal and Oceanpower sources. The use of RE has many potential benefits, such as the reduction in greenhouse gas emissions, the diversification of energy supply, a reduced dependency on fossil fuels and the creation of jobs. As a result, the role of RE continues to increase in the electricity, heating and transport sectors.

Despite recent technological progress, RE is still not ready to compete with conventional sources. Therefore, there are several policy instruments to promote RE (Bode, 2006). On the one hand, among the price-based instruments, Feed-in Tariffs (FIT) guarantee a long-term minimum price for the electricity from renewable sources, since RE producers receive a minimum guaranteed price per kWh, including different fees by technology. A second type of price-based instruments are the Feed-in Premiums (FIP), which consist of a premium paid on top of the market price for renewable producers that sell their electricity on the market. On the other hand, there are quantity-based instruments such as RE-quotas, where certain market participants (e.g. supplier, consumer) are required to supply or consume a minimum quantity of electricity from renewable sources. Furthermore, there are also RE-tenders, where a national authority puts a certain quantity of electricity from renewable sources up for tender. Winners of the tender get a fixed price for the length of the contract. Finally, there are direct subsidies, where (parts of) capital costs are borne by a national authority.

Choosing the right economic support model is critical to the successful development of RE generation. Until 2013, Spain supported the sales price of renewable electricity by establishing either a scheme based on FIT or FIP. In this context, Spain was one of the European countries with the highest share of RE production (9.1% in 2013), surpassed only by Germany (17.5%), Italy (12.2%) and France (12%) (Eurostat, 2015a). Concerning the electricity sector in Spain, the electricity generated from renewable sources accounted for 36.4% of gross electricity consumption in 2013 (Eurostat, 2015b) and 44.64% of total production in the day-ahead electricity market (OMIE, 2015a). Moreover, as Figure 4.3 shows, the electricity produced by renewable sources in the Spanish pool has increased from 26,785 GWh in the year 2000 up to 57,001 GWh in 2007 and 110,237 GWh in 2013.

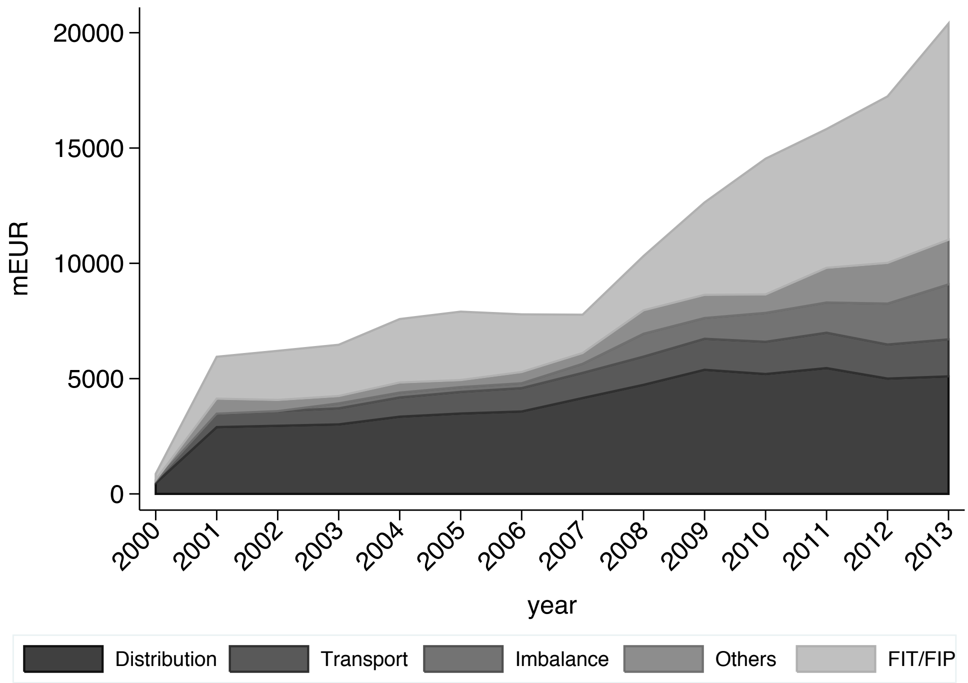
FIGURE 1.1: Production in the Spanish electricity market by technology [GWh]. Period 2000-2013



Source: Own elaboration based on data from OMIE (OMIE, 2015a).

The previous data prove that RE deployment in Spain has been successful. However, RE promotion has increased regulatory costs considerably. Figure 1.2 shows that there has been a sharp increase in the costs of the Spanish incentive system from 2008 to 2013, coinciding with the FIT-FIP period, while other regulatory costs such as distribution or transport remained constant. Hence, the motivation of this research lies in the fact that the environmental and socio-economic benefits of renewable production have to be compared to their economic costs in order to determine the optimal level of public support that these technologies should receive.

FIGURE 1.2: Distribution of regulatory costs in Spain [million EUR]. Period 2000-2013



Source: Own elaboration based on data from CNMC (CNMC, 2014b).

1.0.2 Objectives and structure of the thesis

RE promotion and its cost are at the heart of the energy policy debate in many countries. The question from an economic perspective is how expensive the promotion of renewable sources is. We analyze the Spanish electricity market[2] during the period 2008-2013, where RE production rose by 69% (OMIE, 2015a). This massive introduction of RE had a large impact on many important aspects. One of them is the decrease of the electricity price, as a consequence of the so-called merit order effect. Another relevant effect is the rise of regulatory costs, as a result of an incentive system based on FIT and FIP. A third and important aspect, which has not been studied in the literature, is the induced change in the strategic behavior of the conventional electricity producers. In principle, the entry of new generators in a concentrated market would

[2]We focus on the wholesale electricity market, also known as the day-ahead market, spot market or the pool.

make it more competitive and change the strategic behavior of the incumbents. Finally, the intermittent nature of RE has increased the cost of ancillary services, so a change in consumption patterns could lead to a cost reduction for the electricity system and for consumers.

The present research addresses all these issues empirically and attempts to fulfill a threefold objective. (i) From the consumer standpoint, we compute the economic cost induced by the incentive schemes aimed at RE (Chapters 2 and 3). (ii) From the supply side, we explore the effect of RE on conventional producers (Chapter 4). (iii) From the demand side, we identify posible pricing strategies that could lead to a cost reduction for consumers depending on the elasticity of demand (Chapter 5). The remainder of this document is structured in four standalone chapters.

Chapter 2, "Is green energy expensive? Empirical evidence from the Spanish electricity market", studies how expensive the promotion of renewable sources in Spain during the period 2008-2013 was. FIT have been the main support instrument for electricity from renewable sources in Spain, and they have succeeded in achieving high levels of renewable installed capacity. However, the question is at what cost. In order to quantify it, we first measure the savings due to the spot price reduction driven by the merit order effect and, second, we compute the amount paid as incentives to green energy by the electricity system; the difference between the two is the net cost of green energy to the electricity markets. We present aggregate results for renewable sources as a whole, as well as individual results for each type of technology. We show that at the initial stages, when renewable capacity was low, green energy promotion paid for itself (2008-2009); however, from 2010 on, when renewable production reached a relatively high level, it started to impose a positive net cost on the system. Finally, we found substantial differences among technologies: wind energy implied the lowest net cost, while solar photovoltaic was the most expensive.

Chapter 3, "Switching from Feed-in Tariffs to a Tradable Green Certificate market", presents an alternative regulatory design based on Tradable Green Certificates and analyzes if the concumer costs could have been lower under this incentive scheme. Since FIT do not benefit from market signals, subsidies for some technologies may have been too high to attain the regulator's objectives, thus imposing a great financial burden on consumers. One way out of this problem could be a switch to a market mechanism, particularly in the case of countries where substantial investment in RE is already in place and technologies are at a mature stage. Thus, the main argument of this chapter is that a regulatory system based on Tradable Green Certificates reacts to market changes while FIT do not. We solve a sequential game with strategic interaction between the electricity pool and the Tradable Green Certificates market, focusing on the retailer regulation design that would lead to a demand for green certificates as a function of the certificate price. We then calibrate our theoretical model with data from the Spanish electricity system for the period 2008-2013. Simulations show that a green certificate scheme could both achieve the 2020 targets for renewable electricity and reduce regulatory costs.

Chapter 4, “Evolve or die: Has Renewable Energy induced more competitive behavior on the electricity market?”, evaluates if non-renewable generators changed their bidding strategies as a result of the increasing renewable participation on the electricity market. We construct synthetic supply curves based on the bidding behavior of the year 2008, when the participation of renewable sources in the electricity daily market was starting, and we observe how actual and synthetic electricity prices evolve over time. Simulations show that Combined Cycle producers have clearly reacted to the presence of green sources. During 2009 and 2010, Combined Cycle units bidded at lower prices in order to guarantee their matching in the spot market (accommodating strategy). This behavior is consistent with the hypothesis that firms would react to a less concentrated market with more competitive strategies. However, from 2011 to 2013 Combined Cycle generators changed their strategy and some of them avoided participation on this market by submitting higher price bids (inhibition strategy).

Additionally, the large penetration of intermittent renewable sources (i.e. wind and solar) raises some efficiency problems, since the electricity system is underused in hours where RE is produced at its maximum levels. However, electricity consumers may be sensitive to pricing policies when they are given the right signal, and thus improve the technical efficiency of the whole electricity system. In this sense, Chapter 5, “Pricing policies for efficient Demand Side Management in Spain”, presents a theoretical model based on Time of Use (ToU) pricing. We explore the effect of two sets of elasticities: (i) inter-hour elasticity reflects the willingness to change electricity consumption between peak and off-peak periods and (ii) retailer price elasticity is related to the consumer propensity to switch retailer. We calibrate the model using Spanish data from 2013 and we simulate optimal hourly prices in the current demand conditions for different elasticity values. Results show that, if elasticity is not too low, the price signal to consumers is quite effective in modifying their consumption pattern. The cost for consumers is lower when both inter-hour and retailer price elasticity increase. We observe efficiency improvements for consumers of 18% in winter and 14% in summer. Furthermore, a ToU scheme is always better than a fixed price when the demand is elastic.

Finally, Chapter 6 summarizes the main conclusions derived from this thesis, along with some suggestions for possible future research on the subject.

Chapter 2

Is green energy expensive? Empirical evidence from the Spanish electricity market

2.1 Introduction

Renewable electricity deployment is currently one of the ongoing political priorities in developed countries because of its positive environmental and socio-economic externalities. However, there is widespread debate concerning the economic consequences of large scale renewable participation in electricity markets. On the one hand, investment in Renewable Energy Sources (RES, hereafter) is supported in many forums because of the resulting reduction on the daily market price, due to the merit order effect (Rathmann (2007), Sensfuss et al. (2008) and Felder (2011), among other authors). On the other hand, one of the main criticisms of green generation is the cost imposed on the public support scheme (Morthorst (2000), Menanteau et al. (2003) and Lesser and Sue (2008), among others).

One of the most popular instruments for fostering RES are the Feed-in Tariffs, which are price-based incentive schemes aimed to support RES until renewable technologies approach commercial readiness. With the Feed-in Tariff system, renewable generators sell their electricity in the market under a fixed tariff. These tariffs reduce the risk for investors setting a guaranteed long-term payment for RES. Consequently, Feed-in Tariffs are an effective instrument in overcoming the barriers for RES penetration, whose costs are still higher than those of the conventional sources; and they also result in an increased drive for technological innovation. However, since Feed-in Tariffs do not adjust automatically, getting the appropriate tariff rate is one of the most important and difficult tasks for policy makers. If tariffs are set too high, they would lead to

Windfall profits to renewable generators; but if they are set too low, little or none investment would be issued on RES.

As a consequence of the heavy burden imposed, many countries have already started to reduce or even suppress the incentives to renewable production, particularly to Solar Photovoltaic power. For instance, Solar power subsidies have been reduced in France in 2011 (JORF, 2011) and in UK in 2012 (DECC, 2012), because of the rapidly increasing deployment of Solar installations (at a rate much higher than projected), and they have been phased out for large Solar projects in Canada in 2013 (ME, 2013).

From 2012 German support schemes for new installations will tend to decrease over time, depending on the previous year's additions to renewable capacity. In the case of Solar power, this "degression" rate in Feed-in Tariffs is reviewed monthly and it depends on the excess of the annual capacity expansion target (BGBL, 2011). Additional regulatory changes in Germany include the introduction of a new premium to encourage the direct sale of renewable electricity to the spot market, setting the basis for the transition to a purely market-based regime.[3]

In Australia, subsidies have never supported large scale projects and the focus has mainly been on Solar Photovoltaic for residential producers. However, there have also been cutbacks in the last few years. From 2012 on, new generators connected to the network in New South Wales are no longer eligible for the Solar Bonus Scheme[4] and the incentive will end for all customers in 2016 (NSWGG, 2011). Furthermore, in Victoria Feed-in Tariffs to Solar, Wind, Hydro or Biomass generators under 100 kilowatts in capacity have been lowered in 2013, and from now on, they will be reviewed on an annual basis until 2016 (VGG, 2012).

Feed-in tariffs are used to a limited extent in the United States, where incentives rely on other mechanisms, such as Renewable Portfolio Standards (RPS), tax incentives or net metering. And even in Japan, where Feed-in Tariffs came into operation in July 2012 (Ogimoto et al., 2013), tariffs for Solar Photovoltaic have already been lowered by about 10% in 2013 (METI, 2013).

In Spain, support to Renewable Energy used a combined system of Feed-in Tariffs and Premiums from 2004 to 2013. This incentive scheme was aimed at the so-called Special Regime (SR, hereafter), which includes RES, such as Wind power, Solar Photovoltaic, Solar Thermal, Small Hydropower (capacity lower than 50MW), Biomass, Wastes and Waste treatment; and Cogeneration. The promotion scheme began offering a strong level of incentives, but it has been progressively reduced since 2010, due to the high renewable capacity installed. Finally, new regulation has been introduced in 2013 that substitutes those incentives for subsidies based on a fixed rate of return to investment.

[3] 2012 Amendment of the Renewable Energy Sources Act (BGBL, 2011).

[4] The Solar Bonus Scheme is a Feed-in Tariff aimed to small Solar or Wind generators connected to the grid.

This chapter analyzes the net effect of Renewable Energy and Cogeneration in Spain (from the consumer's perspective) and computes the individual effects of each technology for the period 2008-2013. The question is relevant because the environmental and socio-economic benefits of renewable electricity production have to be compared to their economic costs in order to determine the optimal level of public support that these technologies should receive. Our contribution is to assess, both at the aggregate level and by technology, the economic impact of renewable electricity after the important regulatory changes introduced in mid 2007, when the Spanish-Portuguese market started to operate (in July 2007, specifically). Additionally, in 2008 retail and distribution activities were unbundled, which was an important step in the market liberalization process, facilitating small RES producers to participate in the wholesale market.

Using data for the day-ahead market, we first measure the reduction of the system marginal price (SMP, hereafter) of the spot market, driven by the merit order effect of Electricity from Renewable Energy Sources (RES-E, hereafter). We build an algorithm that computes the outcome of the hourly auction for the electricity wholesale market in two scenarios, with and without renewable sources. The comparison between the two scenarios, for renewable production and Cogeneration as a whole and for each renewable technology separately, allows us to calculate the savings due to the merit order effect. Second, we compute the impact of the incentives on the total cost of the electricity system (from the consumer's perspective). We conclude that there was a breaking point at 2010 and after that year Renewable Energy started to impose a net cost on the system. We also provide results for each technology.

The chapter is structured as follows. Section 2.2 summarizes some of the research evidence on the impact of Renewable Energy production on international electricity markets. Section 2.3 briefly describes the Spanish regulatory framework. Section 2.4 contains the empirical work, including data, specifications and computational algorithm. Simulations and results are presented in Section 2.5. Finally, Section 2.6 discusses the policy implications of the analysis and summarizes the main conclusions of our work.

2.2 The effect of Renewable Energy on international electricity markets

Despite the high cost that RES impose on electricity systems, several studies, both theoretical and empirical, provide evidence of the positive effect of renewable deployment on market prices in different countries. Among the theoretical papers, Jensen and Skytte (2002) were the first authors to point out that as Renewable Energy generation has lower variable costs than conventional fossil-fuel electricity; it could reduce final electricity prices and therefore the total cost of electricity provision.

Empirical studies on the effect of RES-E include regression analysis of historical time series data and electricity price modeling. Jónsson et al. (2010) modeled the spot price dynamics in the Danish electricity market in order to analyze the effect of Wind forecasts on spot prices; they use a non-parametric regression model for the period January 2006-October 2007 and found a significant price effect of Wind generation.

From a different focus, O'Mahoney and Denny (2011) estimated the cost savings in 2009 arising from Wind generation in the Irish electricity market. They found that the total costs for the system would have been around 12% higher had no Wind energy been available and that these savings were significantly greater than the subsidy received for Wind-generated electricity over the same time period.

Similarly, Cludius et al. (2013) estimated the merit order effect of both Wind and Photovoltaic electricity generation in Germany between 2008 and 2012. They showed that for each additional GWh of RES-E, the price of electricity on the day-ahead market was reduced by 1.10 to 1.30 EUR/MWh. They also found that the total merit order effect of Wind and Photovoltaic ranged from 5 EUR/MWh in 2010 to more than 11 EUR/MWh in 2012.

Martin (2004) modeled the impact of Photovoltaic power generation on prices in New England. According to this study, if 1 GW of additional Photovoltaic capacity had been installed in New England in 2002, average wholesale electricity prices would have been reduced by 2 to 5 percent.

Bode (2006) went further and studied the net effect of RES-E on the wholesale market and, based on the analysis of a synthetic power market in Germany, concluded that the power costs for consumers may decrease due to the support scheme, but to what extend power costs decrease depends on the characteristics of the market (e.g. the slope of the supply curve) and the value attached to the "greenness" of renewable sources (e.g. the remuneration paid). Rathmann (2007) and Sensfuss et al. (2008) carried out similar analysis on the merit order effect for Germany.

For the Spanish market, Sáenz de Miera et al. (2008) analyzed the impact of Wind energy in the period January 2005-May 2007. They calculated a reduction in the wholesale price of electricity in the 5-12 EUR/MWh range, with yearly Wind generation of around 20 GWh and net cost savings of more than 2000 million euro over the whole period. However, incentives to renewable electricity generators started to grow exponentially from mid 2007 onwards leading to large changes in investment levels. For the period 2005-2010, Gelabert et al. (2011) estimated the merit order effect of RES and Cogeneration in Spain by OLS regression in first differences. They reported that a marginal increase of 1 GWh of electricity production using renewable sources and Cogeneration is associated with an average price reduction of almost 2 EUR/MWh in the period (3.8 EUR/MWh in 2005, 3.4 EUR/MWh in 2006, 1.7 EUR/MWh in 2007, 1.5 EUR/MWh in 2008, 1.1 EUR/MWh in 2009 and 1.7 EUR/MWh in 2010). Additionally, they assessed that the annual savings due to this price reduction were significantly lower than the annual cost of supporting Renewable Energy. However they did not provide results for each renewable technology separately.

2.3 The regulatory framework in Spain

In 2004, the Spanish Renewable Energy Act[5] provided price-based incentives for new installed capacity of Renewable Energy sources. The support scheme in Spain established that each type of generator in the Special Regime (RES and Cogeneration) received a different reward per MWh. New subsidy levels were established in 2007[6] (higher for Biomass and Cogeneration), as well as a cap and a floor for renewable remuneration. The generosity of the public support system led to a strong increase of investment in renewable production, so that most technologies highly exceeded government targets for the period 2005-2010[7] (see Table 2.1). In an attempt to reduce the costs, incentives were adjusted in 2010[8] including cuts on the Feed-in Tariffs of Solar Thermal electricity and Wind generation, and a cap on the number of hours eligible for support for Photovoltaic installations.

Table 2.1: Evolution of public support to Renewable Energy [million EUR]. Period 2005-2010.

	Wind		Solar PV		Solar TH		Small Hydro		Biomass	
	Actual	Projected	Actual	Projected	Actual	Projected	Actual	Projected	Actual	Projected
2005	613	62	14	9	-	0	112	5	59	5
2006	866	196	40	23	-	6	150	15	75	47
2007	1,004	347	195	47	-	24	147	24	102	147
2008	1,156	510	991	85	-	99	147	36	130	342
2009	1,619	669	2,634	135	-	176	234	49	224	623
2010	1,965	815	2,652	201	185	255	296	60	244	957

Note: Actual data on Solar Thermal not reported until 2010.
Source: Own elaboration, data from CNMC (2014a) (actual values) and the Renewable Energy Plan 2005-2010 [PER 2005-2010] (projected values).

In a context of overcapacity and weak demand, the regulatory changes introduced in 2010 were not deemed sufficient to reduce regulatory costs and, therefore, in 2012[9] new regulation was passed for the temporary suppression of premium and tariffs for new installations. These measures left new RES-E without public support, but existing obligations remained.

[5]Royal Decree 436/2004 (BOE, 2004).
[6]Royal Decree 661/2007 (BOE, 2007a).
[7]Renewable Energy Plan 2005-2010 (MITYC, 2005).
[8]Royal Decree 1614/2010 (BOE, 2010a) and Royal Decree-Law 14/2010 (BOE, 2010b).
[9]Royal Decree-Law 1/2012 (BOE, 2012a).

The last cutbacks were passed in 2013 and affected all renewable production units.[10] The Feed-in Tariffs and Premiums were suppressed to new and existing generation plants. Renewable producers will receive the market price and, if needed, a subsidy to guarantee a fixed rate of return on investment (the yield of the ten-year Spanish Treasury bond plus 300 basis points).[11] Our analysis will be restricted to the period under Feed-in Tariffs and Premiums (2008-2013).

Table 2.2: Evolution of the Equivalent Premium to Renewable Energy and Cogeneration [EUR/MWh]. Period 2004-2013.

	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013
Cogeneration	24.2	17.6	27.4	34.3	35.0	47.6	56.4	57.3	69.4	71.8
Solar Photovoltaic	332.5	340.4	374.1	392.2	388.8	424.6	414.6	324.3	321.1	309.6
Solar Thermal	-	-	-	-	-	-	267.3	240.0	270.1	251.4
Wind	28.1	28.9	37.4	36.4	36.0	42.3	45.6	41.0	42.5	44.0
Small Hydropower	31.7	29.3	36.1	35.6	31.7	43.0	44.1	39.0	40.2	43.1
Biomass	30.5	27.9	35.2	46.7	52.1	74.3	77.6	74.6	82.1	81.4
Waste	18.1	9.2	16.6	19.9	23.2	30.0	29.8	31.3	33.7	30.6
Waste Treatment	26.6	29.4	45.1	51.5	46.9	82.4	81.8	82.4	101.1	108.6
Weighted average Premium	26.5	24.1	34.2	39.2	49.0	75.5	78.1	74.9	83.1	82.0

Note: Data on Solar Thermal not reported until 2010.
Source: Own elaboration, data from CNMC (2014a)

Table 2.3: Evolution of the installed capacity of Renewable Energy and Cogeneration [MW]. Period 2004-2013.

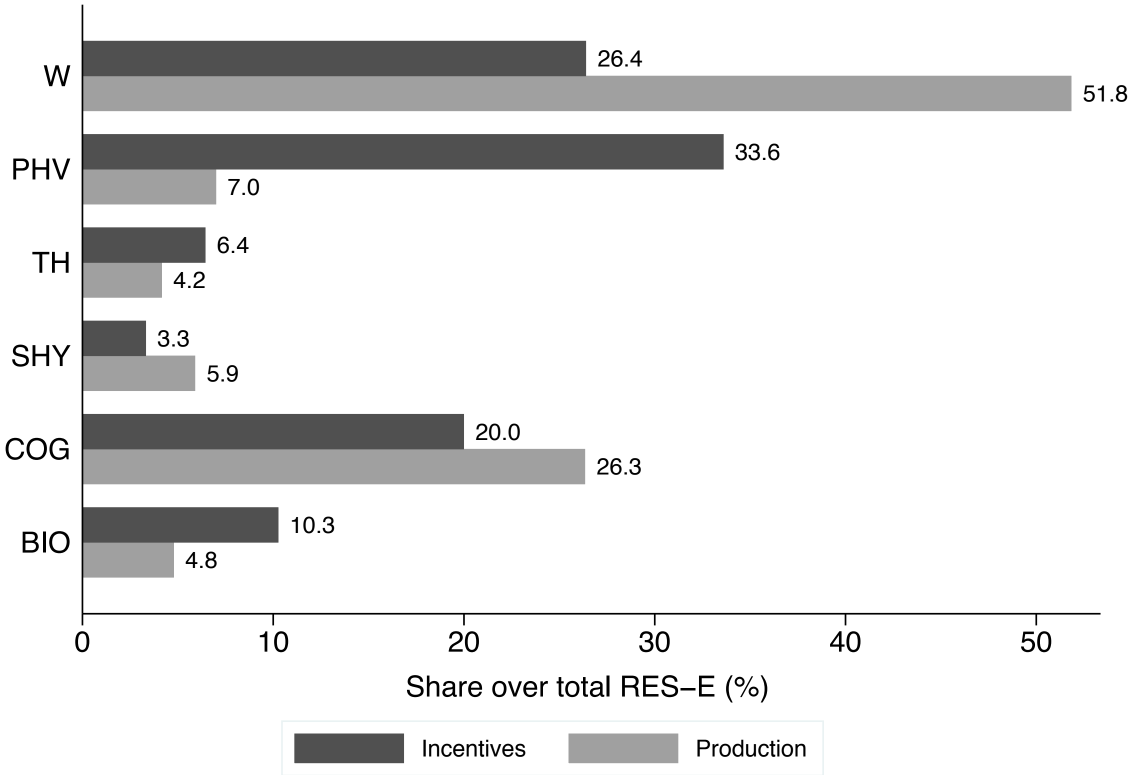
	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013
Cogeneration	5,687	5,689	5,816	6,014	6,060	5,908	6,053	6,161	6,110	5,973
Solar Photovoltaic	24	49	148	705	3,463	3,649	3,856	4,237	4,492	4,640
Solar Thermal	-	-	-	-	-	-	532	999	1,950	2,300
Wind	8,532	10,095	11,897	14,537	16,323	18,843	19,649	21,025	22,493	22,790
Small Hydropower	1,707	1,769	1,899	1,896	1,981	2,013	2,026	2,032	2,035	2,039
Biomass	470	500	541	557	587	665	714	755	837	848
Waste	585	585	579	559	569	570	610	592	603	602
Waste Treatment	474	543	629	533	571	658	658	658	658	633
Total	17,480	19,230	21,509	24,799	29,554	32,304	34,098	36,459	39,179	39,825

Note: Data on Solar Thermal not reported until 2010.
Source: Own elaboration, data from CNMC (2014a)

[10] Royal Decree-Law 2/2013 (BOE, 2013a) and Royal Decree-Law 9/2013 (BOE, 2013b). This reform aimed at the financial stability of the system, which had accumulated a 26 billion euro tariff deficit.
[11] See (Espinosa, 2013).

Table 2.2 provides an overview of the evolution of subsidies to renewable production in Spain from 2004 (when the Feed-in Tariffs and Premiums system was first established) to 2013. We report the equivalent premium (EUR/MWh), which represents the average unit subsidy paid to each technology and it is computed as the annual incentive payment (EUR) over the energy eligible to receive incentives (MWh). Since the technologies with higher premium have increased their capacity and production significantly over the last few years, the (weighted) average equivalent premium has risen notably, reaching 82 EUR/MWh in 2013. As a result of the large subsidies offered, a great amount of renewable capacity was installed and, by the end of 2013, Spain counted with more than 39 GW of renewable sources and Cogeneration (see Table 2.3).

FIGURE 2.1: Distribution of public support and production for RES-E and Cogeneration in Spain [%]. Period 2008-2013.



Note: W=Wind Power, PHV=Solar Photovoltaic, TH=Solar Thermal, SHY=Small Hydropower, COG=Cogeneration, BIO=Biomass/Wastes.
Source: Own elaboration, data from CNMC (2014a) (incentives), OMIE (2015a) and REE (2008, 2009, 2010, 2011, 2012, 2013) (production).

There are substantial differences among technologies. Figure 2.1 represents the share of incentives and production associated to each renewable technology and Cogeneration in the period

2008-2013. From the total amount of public support, 33.6% went to Solar Photovoltaic, 26.4% to Wind power, 20% to Cogeneration, 10.3% to Biomass, 6.4% to Solar Thermal[12] and 3.3% to Small Hydropower. However, the shares on RES electricity production were: 51.8% for Wind power, 26.3% for Cogeneration, 7% for Solar Photovoltaic, 5.9% for Small Hydropower, 4.8% for Biomass and 4.2% for Solar Thermal. This means that higher incentives do not necessarily translate into higher production: Wind power, Small Hydropower and Cogeneration show higher production shares compared to their incentives, whereas Solar technologies and Biomass seem to receive a higher share of public support compared to their participation in energy production.

2.4 Empirical strategy and data

This section describes the data and how we measure the savings due to the merit order effect of renewable sources of energy. Our analysis includes Wind power, Solar Photovoltaic, Solar Thermal, Small Hydropower, Biomass/Wastes and Cogeneration. Even though Cogeneration is not based on renewable sources, we have included it in our study because it is subsidized. Finally, we do not consider Large Hydropower as it does not receive public support.

2.4.1 The Data

We use information provided by the Spanish electricity market operator (Operador del Mercado Ibérico de Electricidad, in short OMIE), the Spanish regulator of energy systems (Comisión Nacional de la Energía/Comisión Nacional de los Mercados y la Competencia, in short CNE/ CNMC and in English National Energy Commission) and the Spanish electricity system operator (Red Eléctrica de España, in short REE) to analyze the net cost of renewable electricity production. The market consists of a pool, as well as a floor for bilateral contracts and a forward market. All available production units that are not bound by physical bilateral contracts are required to present bids for the daily market, where most transactions (about 70%) are carried out in the day-ahead market or spot market (CNE, 2012a). We focus on the base daily operating schedule, which computes the marginal price resulting from the day-ahead market matching and accounts for more than the 80% of the final day-ahead market price (OMIE, 2008, 2009, 2010, 2011, 2012). The other 20% corresponds to intraday market, technical restrictions, capacity payments and other processes of the system operator. The Spanish pool works as a uniform price auction where both suppliers and consumers submit their bids. Sellers represent generating companies and buyers are electricity consumers and retailers who submit bids to purchase electricity on the daily market. Sale and purchase bids can include between 1 and 25 energy blocks in each hour, with different power and price offered in each block.

[12] Data on incentives to Solar Thermal not reported until 2010

Bids in the Spanish pool are submitted the day before by sellers and buyers for each hour and production unit, covering the price range from 0 to 180.3 EUR/MWh. There are two different types of electricity sale bids: simple or complex. Simple offers only state price and energy, whereas complex selling bids incorporate technical or economic conditions such as indivisibility, load gradient, minimum income or scheduled stop (OMIE, 2007). We use data on hourly bids of generators and purchase units for the period 2008-2013, considering complex bids on the supply side. When we build the counterfactual price time series without Renewable Energy, we assume that complex bidding behavior does not change.

Since July 2007, the Spanish and Portuguese markets are interconnected and there is one single hourly price for both markets whenever there is no physical congestion. Otherwise the price differs. When dealing with congestion, we assume that the hours with market splitting in our actual (with RES-E) and counterfactual (without RES-E) time series are the same.

Finally, the system operator provides us with the identification of the different renewable technologies and data on subsidies during the period 2008-2013 have been obtained from the National Energy Commission.

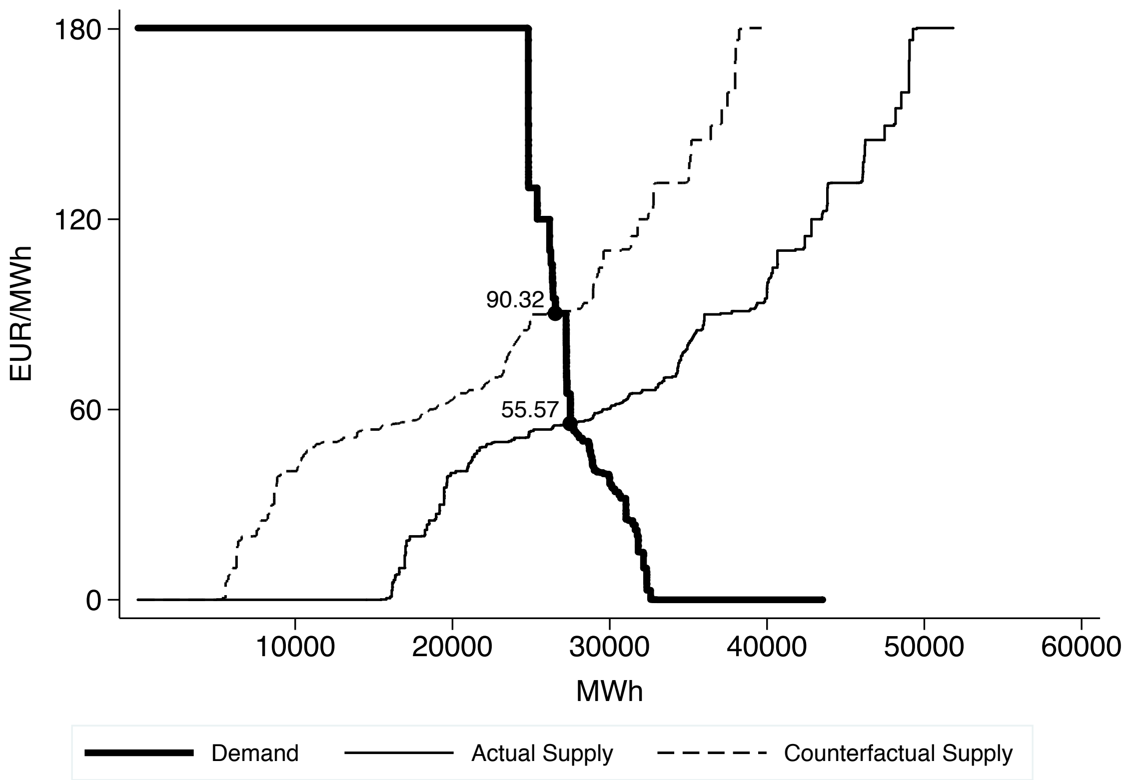
2.4.2 The merit order effect

At each hour, the SMP of the spot market is the result of the intersection of the electricity demand and supply curves and it coincides with the price bid of the last unit that is matched. The SMP determines the revenue for all the electricity produced, independently of the price at which it has been offered. The supply curve is sometimes called the merit order curve.

In general, since the production of electricity from renewable sources usually bids at zero or very low prices, market clearing prices are expected to be lower during periods with higher renewable supply. The increase in renewable production drives units with higher marginal cost out of the market; the supply curve shifts to the right and therefore demand can be met with cheaper technologies, reducing electricity prices. This price reduction is precisely what is called the merit order effect.

Figure 2.2 illustrates the merit order effect. As an example, we reproduce the aggregate supply curve in the Spanish pool for a given day and hour (November 13, 2012. 22:00h). The energy offered at zero prices is higher in the scenario with Renewable Energy (Actual Supply) compared to the scenario without renewable production (Counterfactual Supply). Removing RES-E and Cogeneration has the effect of shifting the supply curve to the left, with the subsequent change in the market clearing price (the marginal price is higher in the scenario without RES-E). In the following sections, we will quantify this merit order effect in terms of prices, revenues and the cost of energy for the electricity system.

FIGURE 2.2: The merit order effect in the Spanish electricity market.
November 13, 2012. 22h.



Note: AS=Actual Supply (with SR), CS=Counterfactual Supply (without SR).
Source: Own elaboration, data from (OMIE, 2015b).

2.4.3 Computational algorithm

We build an algorithm to compute the day-ahead electricity market outcomes under different conditions (see Appendix A for detailed information on the code). Equations 2.1, 2.2 and 2.3 characterize the amount of energy traded and the equilibrium market price on an hourly basis. Equation 2.1 expresses the fact that for each price the quantity traded would be the short side of the market, where $q_{ask}(p_i)$ represents the aggregate volume of ask orders at prices p_i,where p_i=0,. . . ,180 EUR/MWh, and $q_{bid}(p_i)$ represents the aggregate volume of offers at prices p_i. The short side of the market $q_{min}(p_i)$ at high prices would be the demand while the short side at low prices would be the supply. Equation 2.2 computes the quantity traded (q_{traded}) as the maximum of the quantities obtained in Equation 2.1. Finally, Equation 2.3 finds the market clearing price (or market price or SMP) according to the market rules. Quantities are expressed in MWh and prices in EUR/MWh.

$$q_{min}(p_i) = \min\{q_{ask}(p_i), q_{bid}(p_i)\} \tag{2.1}$$

$$q_{traded} = \max_{p_i}\{q_{min}(p_i)\} \tag{2.2}$$

$$p_{traded} = q_{bid}^{-1}(q_{traded}) \tag{2.3}$$

We compute hourly time series for each year by running this algorithm with and without renewable production units. First, we use the algorithm to compute market clearing prices for each hour in the sample period obtaining the Actual Market Price (AMP), and then for a counterfactual situation without renewable sources, the Counterfactual Market Price (CMP). In the counterfactual scenario, we remove renewable generation in the supply curve, leaving demand unchanged. Finally, we use the same procedure to analyze each renewable source separately (i.e. we remove only Wind generators, leaving demand and the rest of the renewable technologies unchanged, repeating this procedure for each technology).

Table 2.4: Evolution of the Reserve Margin in Spain without Renewable Generators (Special Regime). Period 2008-2013.

	Installed Capacity, C_i (GW)	Available Capacity, C_a (GW)	Ratio $\frac{C_a}{C_i}$ (%)	Extreme peak demand, EPD (GW)	Reserve Margin, $\frac{C_a}{EPD}$
2008	62.76	50.12	79.87	42.96	1.17
2009	62.75	50.36	80.25	44.44	1.13
2010	64.29	53.87	82.24	44.12	1.20
2011	63.19	52.16	82.54	44.11	1.18
2012	62.72	49.42	78.79	43.01	1.15
2013	62.66	51.21	81.73	39.96	1.28
Minimum Required					1.10

Note: Only Large Hydro power, Combined Cycle, Nuclear and Coal.
Source: Data on installed capacity and demand in REE (2008, 2009, 2010, 2011, 2012). Data on availability coefficients in Order IET/843/2012 (BOE, 2012b), Order ITC/3353/2010 (BOE, 2010c), Order ITC/3519/2009 (BOE, 2009b) and Order ITC/1659/2009 (BOE, 2009a)

In order to build the counterfactual scenario, we assume that the non-renewable capacity is the same as in the actual scenario. It could be argued that without incentives to Renewable Energy, investors would have launched other projects in different technologies. However, this is unlikely given that the Spanish electricity market exhibits high reserve margins, even excluding renewable capacity (see Table 2.4). Additionally, we assume that fossil-fuel generators bidding in AMP scenario also hold in CMP scenario. This assumption will hold as long as market power is not a serious problem and bids reflect firm production costs.

Concerning emission abatement costs, following Chen et al. (2008) we consider that producers internalize them in their bids. This means that our price change already reflects this effect and emission costs are therefore included in our results. This holds true as long as carbon prices do not change from their current levels to the counterfactual scenario. This is a reasonable assumption since emission trading markets clear at an international level, and the effect of a single country, like Spain, will not affect carbon prices.

We compute all the hourly prices, actual and counterfactual, for the period 2008-2013.[13] The comparison of real and counterfactual outcomes allows us to quantify the effect on prices of the heavy investment in renewable sources. In order to see how results change with the demand profile, we also classify the hours of the day into three different periods, according to energy demand in each of them: low-demand, mid-demand and peak-demand.

2.5 Results and Discussion

2.5.1 The effect of renewable production on the market clearing price

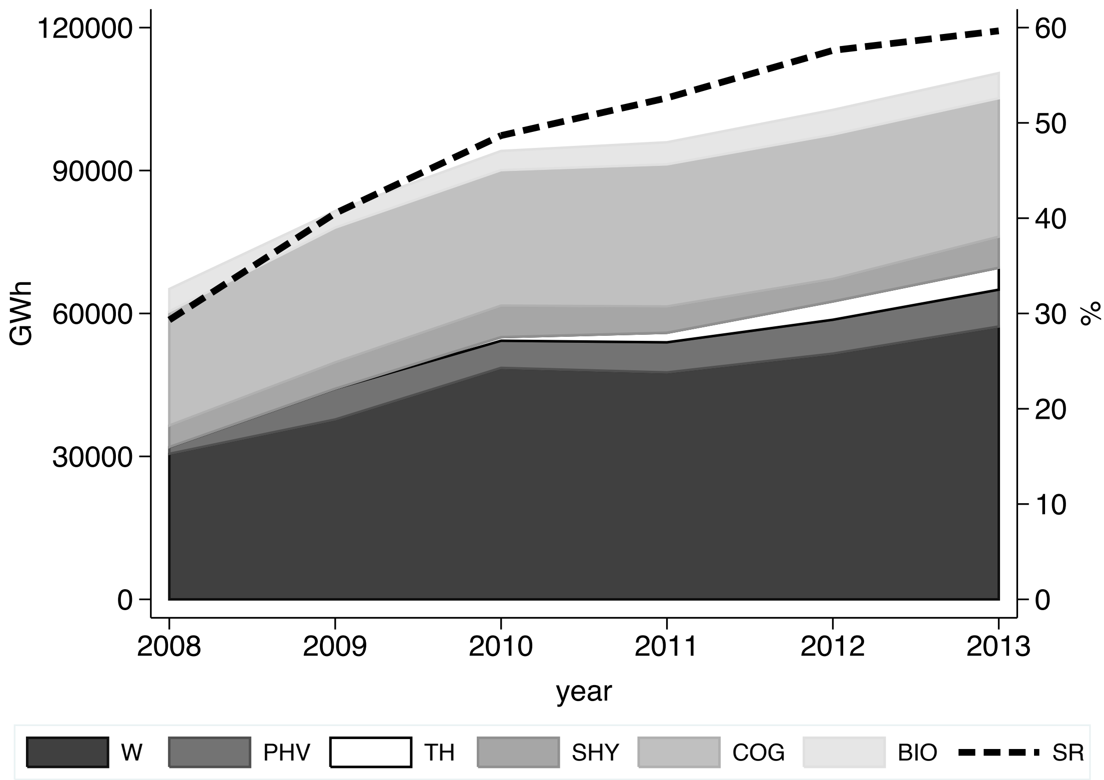
Undoubtedly, the evolution of green energy participation in the electricity market makes it clear that regulation had a significant impact on Renewable Energy deployment in Spain. As Figure 2.3 shows, Renewable Energy and Cogeneration ranged from 65,376 GWh in 2008 (29% of total production in the pool) to 110,455 GWh in 2013 (more than 60% of total production in the pool). Observing each source separately, all of them exhibit an upward trend, with Wind power accounting for half of renewable production, followed by Cogeneration, with around 30%. Additionally, Photovoltaic energy has shifted to higher shares, outperforming Small Hydropower and Biomass since 2011. Finally, Solar Thermal shows modest growth in the last two years of the period under study.

The effect on prices of this rapid increase in production share is presented in Figure 2.4 (monthly average prices) and Table 2.5 (weighted average prices). Figure 2.4 illustrates the hourly price evolution for the period 2008-2013, where the price gap with and without Renewable Energy is evident. The fact that Renewable Energy units bid at the pool at zero prices guarantees that they are always matched and this has the effect of displacing more expensive technologies and decreasing market prices. According to Table 2.5, average price reductions are in the 25-45 EUR/MWh range each year, depending on weather conditions that affect Wind and Solar production and market conditions. These price reductions are rather high due to the high rate

[13] See (Ciarreta et al., 2012a,b) and (Espinosa and Pizarro-Irizar, 2012).

of growth of RES production in Spain in these years. The lowest value corresponds to the year 2011, a period where Wind production was under the average in Spain (REE, 2011), which led to a higher actual market price and, at the same time, reduced the counterfactual marginal price (less Wind implies less production at zero prices). The highest value corresponds to the year 2009, characterized by a substantial increase in Hydro, Wind and Solar energy (REE, 2009).

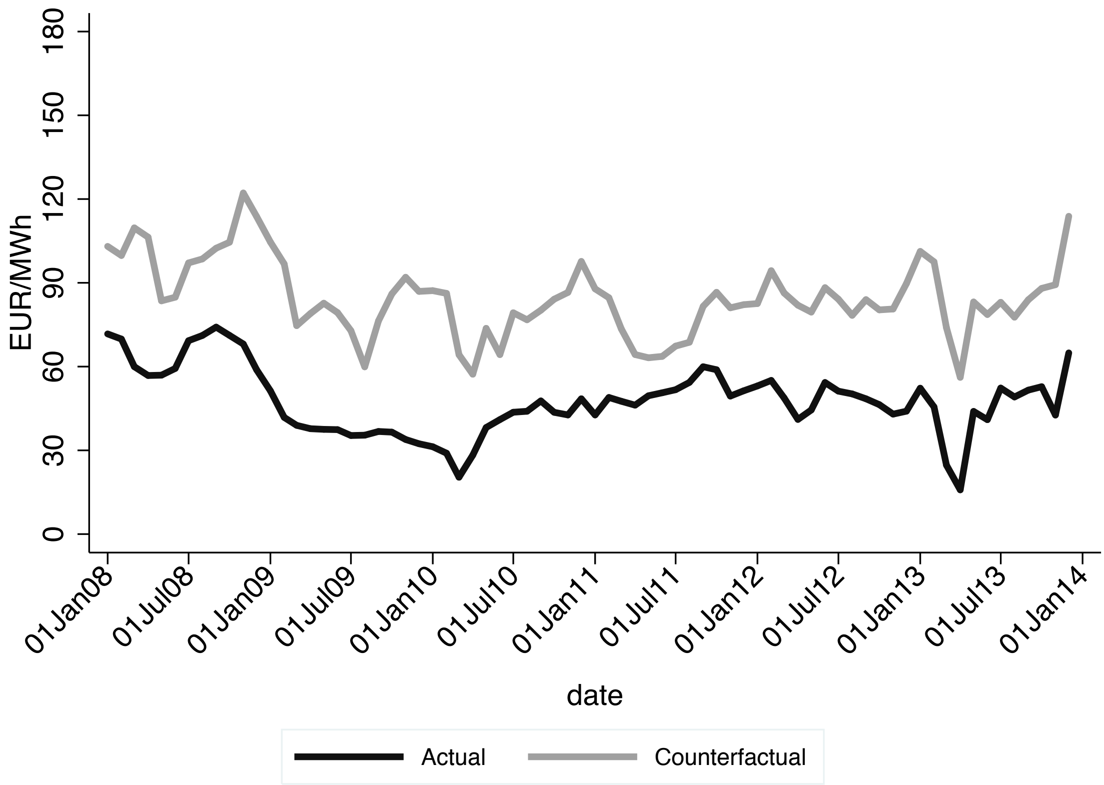
FIGURE 2.3: Evolution of renewable production and Cogeneration in the Spanish pool. Period 2008-2013.



Note: Left axis (Production by technology, GWh): W=Wind Power, PHV=Solar Photovoltaic, TH=Solar Thermal, SHY=Small Hydropower, COG=Cogeneration, BIO=Biomass/Wastes. Right axis (Share of RES-E and Cogeneration over total production, %).
Source: Own elaboration, data from OMIE (2015b) and REE (2008, 2009, 2010, 2011, 2012, 2013)

We observe that the presence of RES-E and Cogeneration in Spain decreases market prices in our period of analysis, 2008-2013. However, it would be interesting to study if the effect on prices is just temporary or it affects the trend. It is argued (Gelabert et al., 2011) that when the decrease in electricity prices takes place, it reduces the long-term signal for investment and thus deters future investments, bringing about a subsequent increase in electricity prices due to restricted supply. Nevertheless, the current scenario of excess capacity and weak demand suggests that such price increases are unlikely in the short/medium term.

Figure 2.4: Evolution of the System Marginal Price in the actual scenario (with Renewable Energy and Cogeneration) and in the counterfactual scenario (without Renewable Energy and Cogeneration). Period 2008-2013.



Source: Own elaboration, data from OMIE (2015b).

Table 2.5: Market price reduction due to renewable production and Cogeneration [EUR/MWh]. Period 2008-2013.

	2008	2009	2010	2011	2012	2013
Actual Market Price (A)	65.55	38.01	38.01	50.80	48.50	44.26
Counterfactual Market Price (B)	101.90	82.68	78.43	75.67	84.41	85.46
Market price reduction(B-A)	36.35	44.67	40.42	24.87	35.91	41.20

Note: The market price includes only the day-ahead market. Intraday market, technical restrictions, capacity payments and other processes of the system operator have not been considered. We compute weighted average prices.
Source: Own elaboration, data from OMIE (2015b).

Regarding demand, the impact of renewable sources differs depending on the hour. Table 2.6 shows that the price reduction effect due to Renewable Energy tends to be higher with high demand, where renewable generation substitutes for thermal production, leading to a greater use of renewables. In peak (off-peak) hours the SMP is determined by a high (low) cost technology, and as a result the merit order effect is greater the higher the demand is. This effect could also explain why the merit order effect in 2011 and 2012 is lower than in the two previous years. Electricity demand is very sensitive to economic conditions and the strong contraction in the economic activity of the country has affected the demand of energy and implied a lower merit order effect.

Table 2.6: The effect of the demand on the market price reduction due to the SR in Spain [EUR/MWh]. Period 2008-2013.

	2008	2009	2010	2011	2012	2013
Low demand hour (hour 6)	23.71	16.53	20.44	17.61	30.15	33.54
Mid demand hour (hour 11)	42.55	59.14	44.76	25.36	35.34	42.33
High demand hour (hour 21)	41.55	63.58	60.24	35.92	40.41	46.92

Source: Own elaboration, data from OMIE (2015b).

As regards supply, we assumed that the bidding behavior of traditional energy sources did not change after the introduction of Renewable Energy. Nevertheless, our results would be underestimated (the price reduction would be even higher than calculated) if traditional sources now bid at lower prices in order to avoid being displaced from the market by renewable units (see Chapter 4). Our assumption that bidding has remained constant corresponds to a situation where market power is not a serious issue. In any case, if the incumbents had reacted to the introduction of new generators, this reaction would have brought lower prices as a response to the higher level of competition in the market and this effect would add to the merit order effect.

2.5.2 The net cost of Renewable Energy

In the previous section, we checked that Renewable Energy implies savings for the system in terms of a lower electricity price. These savings are computed in Table 2.7, comparing the generators' revenue in the actual scenario (row A) to the revenue in the counterfactual (row C); the difference between the two is the reduction in the cost of electricity for the system. However, renewable production has also required public support. The total amount of subsidies is included in row B. Table 2.7 shows that renewable generation deployment leads to a decrease in market prices and reduced costs for the system (C-A) but, on the other hand, it has been costly in terms of subsidies (B). The net cost of renewable sources of energy is thus (A-C+B). We may conclude from the results in Table 2.7 that after 2010, the benefits coming from the merit order effect associated to renewable production were not able to compensate for the subsidies received, contributing to an increasing deficit.

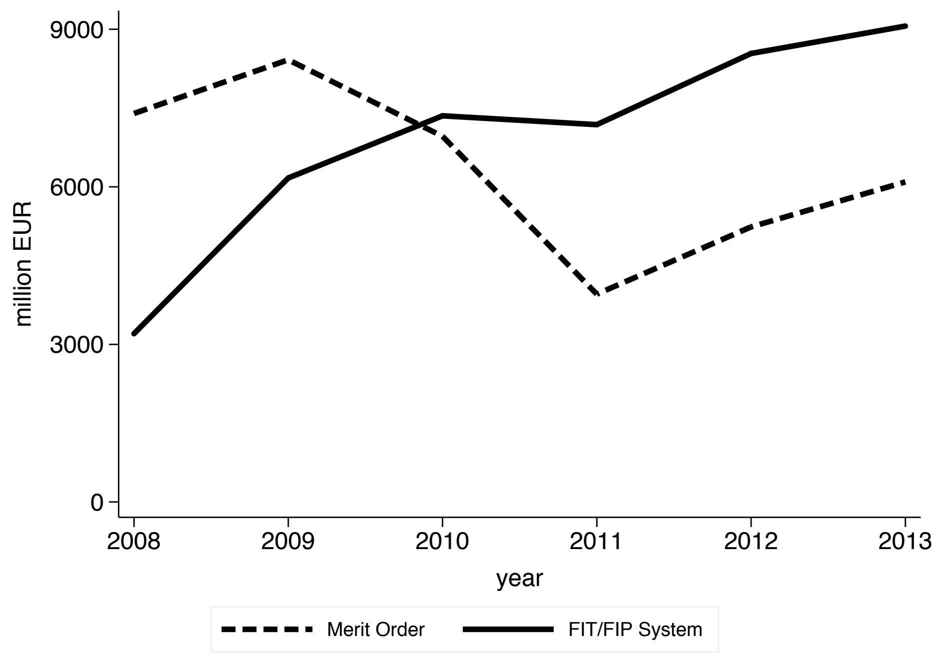
Table 2.7: Net Costs of renewable production and Cogeneration in Spain [million EUR]. Period 2008-2013.

	2008	2009	2010	2011	2012	2013
Day-ahead market (A)	14,563	7,646	7,349	9,260	8,649	8,195
Public support system (B)	3,204	6,169	7,352	7,184	8,539	9,060
Day-ahead market without SR (C)	21,960	16,065	14,311	13,217	13,886	14,289
Net Costs (A+B-C)	-4,193	-2,260	390	3,227	3,302	2,966

Source: Own elaboration, data from OMIE (2015b) (A, C) and CNMC (2014a) (B).

This result may also apply to other countries. As long as the savings due to the merit order effect decrease over time and the cost of the subsidies increase, the two trends will cross at some point and the net cost of the subsidies will become positive (See Figure 2.5).

Figure 2.5: The merit order effect vs. the cost of the subsidies [million EUR]. Period 2008-2013.



Note: The dashed line represents the evolution of the benefits coming from the merit order effect. The solid line represents the evolution of the costs of the public support scheme.
Source: Own elaboration, data from OMIE (2015b) (merit order effect) and CNMC (2014a) (cost of the public support system).

Additionally, Table 2.8 computes the level of subsidies needed to avoid this break-even point, that is, no gain and no loss in the system. The Virtual Average Premium is obtained as the maximum subsidy level in EUR/MWh for which the market savings due to renewable sources and Cogeneration are still able to compensate for the incentives paid. We find that, given the amount of energy of the SR traded in Spain, the incentive level given during the years 2008 and 2009 could have been higher (64.14 EUR/MWh higher in 2008 and 27.65 EUR/MWh in 2009) and still RES and Cogeneration would have not resulted in extra costs for the system. On the contrary, from the year 2010 on, the public support scheme has been excessive in Spain and premiums should have been lower in order to attain a sustainable system (4.85 EUR/MWh lower in 2010, 33.64 EUR/MWh in 2011, 32.14 EUR/MWh in 2012 and 26.86 EUR/MWh in 2013).

The SMP reduction due to the merit order effect of renewable production and Cogeneration was lower in 2011 and 2012 than in former years. Although this evolution is partly due to the economic crisis, it remains true that price reductions are necessarily bounded and the cost of the subsidies, as they were designed, was increasing over time with the higher penetration of renewable sources in the spot market.

Table 2.8: Subsidy level needed to avoid the break-even point [EUR/MWh]. Period 2008-2013.

	2008	2009	2010	2011	2012	2013
Actual Average Premium (A)	49.01	75.46	78.13	74.89	83.12	82.03
Virtual Average Premium (B)	113.15	103.11	73.28	41.25	50.98	55.17
Δ Premium (B-A)	64.14	27.65	-4.85	-33.64	-32.14	-26.86

Source: Own elaboration, data from OMIE (2015b) and CNMC (2014a).

Finally, another element that raises the costs of the system is the intermittency and variability of certain renewable technologies, such as Solar or Wind power. The intermittency of RES has created a need to maintain a fleet of sufficiently flexible capacity resources both now and in the future. In other words, the need for flexible capacity resources increases with the level of intermittent resources. This implies adding a significant amount of flexible ramping and capacity products. As a consequence, the weight on the final price of adjustment services, that is, ancillary services and capacity payments, has been rising over time (see Table 2.9), as the presence of intermittent technologies became more important (in 2008 the share of RES-E in the day-ahead market was about 30% and in 2013 it was 60%). Ancillary services include technical restrictions, regulatory band and system operations. They are services to ensure security of supply under suitable conditions of security, quality and reliability. Capacity payments were established with the twofold aim of guaranteeing security of supply (investment incentive) and reserve margin (availability service). They support back-up technologies, such as Combined Cycles, since their participation in the spot market was being reduced by the presence of RES (Villaplana, 2012). However, this chapter only focuses on the direct effect of the presence of RES-E and Cogeneration on the day-ahead market and we do not take into account the cost of other services. We leave this analysis for further research.

Table 2.9: Weight of the price components on the final price [%]. Period 2008-2013.

	Day-ahead	Market Ancillary services	Capacity payments
2008	94.60	3.78	1.62
2009	88.07	6.22	5.75
2010	85.02	8.37	6.75
2011	84.64	5.33	10.13
2012	82.14	7.74	10.19
2013	80.14	9.57	10.40

Source: Own elaboration, data from OMIE (2008, 2009, 2010, 2011, 2012).

2.5.3 Individual effects by technology

Each technology is analyzed separately in this section to check whether there is also a breaking point for each source.

Table 2.10 illustrates the merit order effect by technology. Except for 2011, when Wind production was abnormally low, this technology alone has reduced the market price by 10-17 EUR/MWh (17-40%) and Cogeneration has reduced prices by 5-10 EUR/MWh (10-22%).

Figure 2.6 shows graphically the effect of each renewable source for the period 2008-2013. We remove each technology separately from the supply side and measure the effect on market price and equivalent premium. The equivalent premium represents the average unit subsidy paid to each technology and it is computed as the annual amount of public support (EUR) over the energy eligible to receive incentives (MWh). The horizontal axis represents the reduction in the equivalent premium that each technology entails (negative values imply an increment in the equivalent premium) and the vertical axis represents the reduction in the system marginal price implied by each technology. Finally, the gray area represents the range where a certain technology has the effect of decreasing the market price and the equivalent premium.

Table 2.10: Market price reduction by the main renewable technologies [EUR/MWh]. Period 2008-2013.

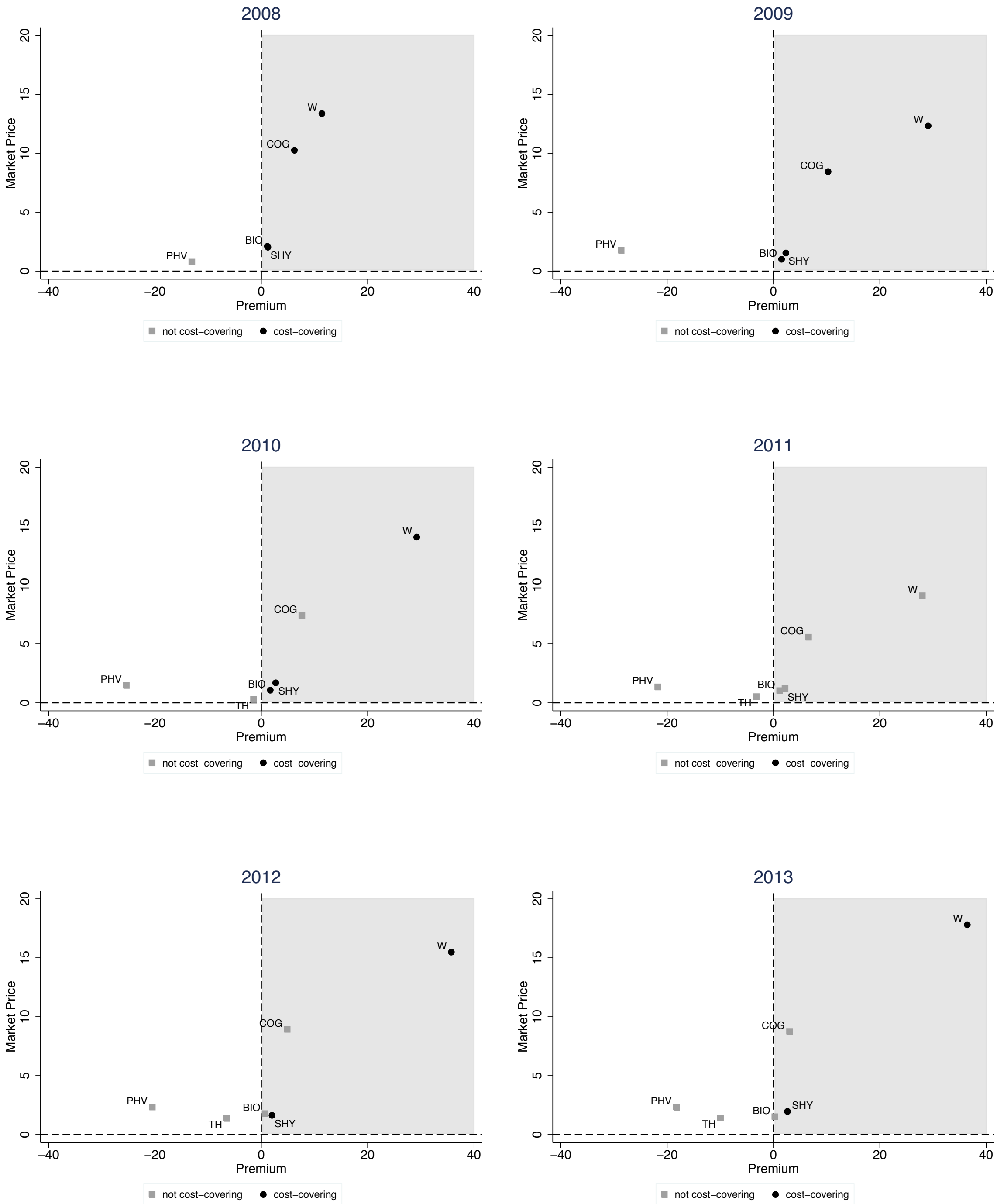
	2008	2009	2010	2011	2012	2013
Wind Power	13.37	12.33	14.06	9.08	15.48	17.80
	(20.40%)	(32.44%)	(36.99%)	(17.87%)	(31.92%)	(40.22%)
Solar Photovoltaic	0.77	1.77	1.48	1.35	2.34	2.31
	(1.17%)	(4.66%)	(3.89%)	(2.66%)	(4.82%)	(5.22%)
Solar Thermal	-	-	0.29	0.52	1.37	1.41
	-	-	(0.76%)	(1.02%)	(2.82%)	(3.19%)
Small Hydropower	2.03	1.54	1.70	1.20	1.63	1.96
	(3.10%)	(4.05%)	(4.47%)	(2.36%)	(3.36%)	(4.43%)
Cogeneration	10.25	8.44	7.40	5.57	8.93	8.74
	(15.64%)	(22.20%)	(19.47%)	(10.96%)	(18.41%)	(19.75%)
Biomass/Wastes	2.11	1.01	1.07	1.03	1.77	1.61
	(3.22%)	(2.66%)	(2.82%)	(2.03%)	(3.65%)	(3.64%)

Note: Data on Solar Thermal not reported until 2010.
Source: Own elaboration, data from OMIE (2015b).

The pattern is quite similar for all the years. We observe that all technologies contribute to reduce market prices, with Wind power being the technology with the largest impact on the merit order, followed by Cogeneration. Solar technologies (Photovoltaic and Thermal) have the lowest effect in lowering market prices. Regarding the equivalent premium, Solar technologies are the only ones that increase the equivalent premium (negative values in the x-axis mean an increment in the premium), reflecting that even though they do not produce large amounts of energy, they receive large incentives. In fact, Solar technologies are never in the gray area during the period under analysis.

However, not all technologies located in the gray area are classified as cost-effective, despite their positive merit order effect. Cost effectiveness depends on the relationship between the amount of energy traded for each technology and the incentives they receive. In Figure 2.6, the bullet symbol (black) corresponds to the cost-covering technologies and the square symbol (gray) represents the ones not covering cost. Differences can therefore be observed over time: whereas in 2008 and 2009 all technologies were cost-effective but Solar Photovoltaic, in 2010, 2012 and 2013 only Small Hydro and Wind power were able to cover their regulatory costs with the market price reduction they entailed and, furthermore, in 2011 not a single technology was cost-covering (a consequence of the lower merit order effect due to lower rainfall and Wind production coupled with weak demand).

FIGURE 2.6: Market savings vs. Incentives by technology [EUR/MWh]. Period 2008-2013.



Note: Every point on the graph stands for a different technology, the horizontal axis represents the reduction in the average equivalent premium by the corresponding technology (negative values imply an increment in the average equivalent premium). The vertical axis represents the reduction in the system marginal price by each technology.

Source: Own elaboration, data from CNMC (2014a) (incentives), OMIE (2015a) and REE (2008, 2009, 2010, 2011, 2012, 2013) (production).

Finally, Table 2.11 reports the percentage of the incentives that the different renewable sources were able to cover thanks to the merit order effect. Magnitudes over 100% (black bullet in Figure 2.6) mean that the technology was able to cover the costs of the subsidies, that is, the market costs if they did not participate in the pool would be higher than the incentives they actually received. On the contrary, values under 100% (gray square in Figure 2.6) imply that the technology imposed a net cost on the system, since the market savings could not pay for the public support it received. The higher the share over 100%, the more cost-effective the source is. Some technologies, such as Solar Photovoltaic and Solar Thermal have not been able to cover their costs in any of the years (values lower than 30%). Wind power and Small Hydro power, on the other hand, have proved to be quite efficient in repaying for their costs, even providing savings to the system. Finally, the merit order effect of Cogeneration and Biomass/Wastes covered their subsidies in the first years, but in the last year they only covered 65% and 62%, respectively.

Table 2.11: Coverage of the public support costs by renewable production and Cogeneration in Spain [%]. Period 2008-2013.

	2008	2009	2010	2011	2012	2013
Wind Power	257	152	109	72	110	104
Solar Photovoltaic	17	16	10	9	13	14
Solar Thermal	-	-	27	18	21	15
Small Hydropower	293	121	114	93	139	121
Cogeneration	236	102	78	52	66	65
Biomass/Wastes	274	131	123	70	76	62
Total	231	137	95	55	61	67

Note: Data on Solar Thermal not reported until 2010.

Source: Own elaboration, data from OMIE (2015b).

2.6 Conclusions and Policy Implications

This chapter analyzes the effect of Renewable Energy production in the Spanish electricity market in the period 2008-2013 from an economic perspective (from the consumer's perspective). The main goal is to quantify its economic impact, both at the aggregate level and by technology, in order to determine how expensive Renewable Energy is. The main focus of this study is the economic assessment of the net costs of RES-E. The question is relevant because the environmental and socio-economic benefits of RES-E have to be compared to their economic costs in order to determine the optimal level of public support that these technologies should receive.

Overall, the combination of Feed-in Tariffs and Premiums has been a cost-effective instrument to promote renewable electricity in Spain, since they contributed to both (i) the take-off of green participation in the pool, from 29% in 2008 to 60% in 2013, and (ii) a significant reduction of the daily market price, around 25-45 EUR/MWh, depending on the year. Nevertheless, this merit order effect could be underestimated, if traditional sources would bid now at lower prices in order to avoid being displaced from the market by renewable units.

On the other hand, this energy might seem rather expensive for the electricity system in terms of RES-E subsidies. However, our results indicate that green energy pays for itself up to a point (depending on the amount of green energy traded) and we empirically show that Spain has already passed that breaking point. According to our results, although there were savings during the first two years of the analysis, the price contraction due to green sources from 2010 on was not able to overtake the increase in the incentives. This raise in regulatory costs was mainly due to the boost of Renewable Energy production at the pool combined with generous Feed-in Tariffs and Premiums, which led to high incentive payments and contributed to a large tariff deficit. Additionally, since electricity demand is very sensitive to economic conditions, the strong contraction in the economic activity of the country affected the demand of energy and implied a lower merit order effect in the period 2011-2013 and, consequently, lower market savings due to Renewable Energy.

Facing this scenario, the Spanish system of incentives was not sustainable and this led to significant changes in energy policy in 2013, when the system of Feed-in Tariffs and Premiums was cancelled. In an attempt to tackle the tariff deficit in Spain, the aim of the new regulation is to cover producers' costs and attain reasonable profitability. However, the lack of incentives and the changing legal framework will soon become apparent with new Renewable Energy installed capacity coming to a standstill.

Nevertheless, we observe significant differences when analyzing each renewable source separately. We show that not all renewable technologies are expensive as they can have a negative net cost. In this sense, premiums to Wind energy and Small Hydro power did not bring about any loss to the Spanish electricity system from 2008 to 2013, with the exception of the year 2011, where both rainfall and Wind were lower than average; and similarly Biomass was not a great burden.

Finally, according to empirical studies on learning curves in energy production, the reduced technology costs allow support policies to be lowered over time (Wiesenthal et al., 2012), while providing sufficient incentives for Renewable Energy deployment. Consequently, some renewable technologies (Wind, Small Hydro) might be mature enough at some point to compete in the market without a strong level of incentives (Ciarreta et al., 2014b). Another important question is the design of the incentive mechanism, since not all the public support systems are equally effective in providing incentives for investment in Renewable Energy sources at the possible least cost. This precisely is what we analyze in Chapter 3.

Chapter 3

Switching from Feed-in Tariffs to a Tradable Green Certificate system

3.1 Introduction

European Directive 2009/28/EC laid down the guidelines for state aid and incentives for Renewable Energy in Europe until 2020. The main priority was initially to enhance the deployment of Renewable Energy Sources (RES) and there was less concern over the economic consequences that a large penetration of renewable electricity would have on the wholesale markets or the efficiency of the incentive schemes. The regulatory design of electric power systems was thus conceived without taking into account the economic impact of electricity from RES (RES-E). Under this regulatory framework, the deployment of RES-E in the European Union (EU) has been much more successful than estimated in terms of green installed capacity.[14]

This chapter evaluates the incentive schemes for renewable electricity sources. In particular, we explore markets for Tradable Green Certificates (TGC) as an alternative to Feed-in-Tariffs (FIT). TGC is a market-based system and therefore able to adapt to changes in the RES cost structure over time. We first build a theoretical model that formalizes the interaction between the electricity market and the TGC market and allows us to compare different incentive schemes. There is a decreasing demand for certificates on the TGC market coming from retailers, through a quadratic penalty function for non-compliance with the RES-E target; whereas the supply comes from the production decisions of green generators. The price of the certificate provides the incentive for Renewable Energy and reacts to market conditions.

[14]According to the previsions of the Member States' Renewable Energy Action Plans and the EU industry roadmap, the share of renewable electricity generation in the EU is expected to be between 34% and 42% by 2020 (EREC, 2011; EWEA, 2011).

From a theoretical point of view, a FIT system could be equivalent to a TGC market, since in principle and as long as market conditions (demand, costs ...) were observable, the regulator could fix FIT, and the regulatory parameters in a TGC market, at the optimal level. We argue that the nonobservability of market conditions makes TGC a preferable incentive scheme and we implement the model using actual data of the Spanish electricity market to illustrate this point.

The main argument of the chapter is that a TGC-based regulatory system reacts to market changes while a FIT-FIP (Feed-in Tariffs-Feed-in Premiums) incentive scheme does not. We compare the actual evolution of an electricity market under FIT-FIP to several counterfactuals under TGC in order to see how it reacts and to establish the importance of this TGC advantage. We first calibrate the model to obtain cost and demand parameters to build the counterfactuals, and then derive the relevant regulatory parameters so that the incentives under TGC equal those that were in place for a given year under FIT-FIP. We analyze the interactions between the electricity market and the certificate market as an important element, as FIT and TGC may have different side effects on the generation market.

Our simulations show the functioning of TGC as an RES-E promotion instrument in Spain, where the FIT-FIP system has been the key support instrument for years, the presence of renewable sources is high and there is no need for additional capacity in the electricity system.

The chapter is structured as follows. Section 3.2 describes the role of the different incentive schemes to promote RES-E, including their advantages and drawbacks, and compiles a literature review of TGC markets. Section 3.3 develops a theoretical model to analyze the interaction between the electricity pool and the TGC market considering perfect competition in both markets. The highlight of the model is the design of the penalty function, which achieves a decreasing demand for certificates. Then, we calibrate our TGC model with data from the Spanish electricity system for the period 2008-2013 in Section 3.4, and parameters for the numerical implementation are obtained. Simulations using counterfactual scenarios for the model based on Spain are presented in Section 3.5. Section 3.6 then discusses the policy implications of a system based on TGC compared to FIT. Finally, Section 3.7 summarizes the main conclusions of this chapter and provides further research perspectives.

3.2 The role of the incentives

3.2.1 Price-based vs. quantity-based mechanisms

Despite recent technological progress, new or emerging RES-E is still not profitable on a free market, due to its high investment costs compared to conventional sources. Support instruments are hence introduced to help the penetration of renewable technologies and improve market efficiency, internalize external costs, accelerate investments in research and provide temporary incentives for early market development as such new technologies approach commercial readiness (Sims et al., 2003). Additionally, RES-E support systems increase the amount of RES-E produced through the merit order effect, since electricity production from conventional fossil-fuel sources, which are the marginal plants, is then substituted by RES-E and the wholesale price of electricity drops.[15] However, the net effect on the consumer price level will depend on the way in which the RES-E support system is financed (Rathmann, 2007) and thus the choice of the promotion instrument and how it is implemented is crucial.

In this sense, RES-E has been promoted in most European countries mainly through price-based mechanisms, such as FIT or FIP; and quantity-based mechanisms, including TGC or quotas. Under FIT schemes, RES-E producers may sell their entire output at a guaranteed price that is set above the wholesale market clearing price. This higher price allows the generators of some RES of energy to cover the higher costs of this type of energy and stay on the market. The main difference between FIT and FIP is that the incentive level under the FIT system is fixed, whereas under the FIP scheme renewable generators get a guaranteed premium, which is lower than the FIT, plus the price of the pool. TGC systems, however, rely on market mechanisms for resource allocation and thus are not fixed in advance. As Figure 3.1 shows, most countries in Europe use price-based schemes; specifically, 21 out of 27 Member States use FIT at least for some technologies and seven use FIP as the main or secondary financial tool supporting RES-E; whereas only six countries use quantity-based instruments[16] (COM(2011) 31 final). Finally, other instruments, such as investment grants, tax exemptions and fiscal incentives are used as secondary instruments in many countries, but not as leading support systems.

If we compare both main instruments in Europe, the FIT approach is generally more popular than TGC, as it guarantees the price and removes the risk from investors in renewable generation; whereas the TGC scheme may involve higher uncertainties, due to market outcomes, and investors consequently require higher payments (Neuhoff, 2005). This conclusion may partly rest on the European experience, where FIT regimes in Germany or Spain outperformed the TGC scheme in other countries, such as the United Kingdom (Buttler and Neuhoff, 2008). However, it is argued that FIT may serve mainly to shift the risk to other agents (i.e. consumers) but does not reduce it for society as a whole. Moreover, the problem with FIT is the need to set the tariff at an appropriate level, with the risk that it may be too high, creating excessive rents for some generators, or too low, restricting investment (Green and Vasilakos, 2011). In fact, the

[15]For an analysis of the effect of renewable electricity production in the Spanish electricity market see Ciarreta et al. (2012a,b, 2014a) and for an analysis of the effect of regulation in the electricity prices in Spain see Ciarreta and Espinosa (2012); Ciarreta and Pizarro-Irizar (2014).

[16]Italy abolished the green certificate system for new producers after 2013. Norway and Sweden have had a common green certificate market since 2012.

difficulties that regulators face when designing the optimal level of incentives is one of the main problems of the price-based policies.

FIGURE 3.1: RES-E support mechanisms in the EU Member States.

(A) FIT or FIP (B) Green Certificates (C) Other Instruments

Source: Own elaboration based on COM (2011).

Outside the EU, other countries (e.g. Brazil, China, Morocco, Peru and South Africa) rely on Renewable Energy Auctions to procure RES-E at moderate cost. These auctions work as follows (IRENA, 2013): First, the government issues a call for tenders to install a certain capacity of RES-E. Second, project developers who participate in the auction submit a bid with a price per unit of electricity at which they are able to realize the project. Finally, the government evaluates the offers on the basis of the price and other criteria and signs a Power Purchasing Agreement (PPA) with the successful bidder, whose term often is set at between 15 and 20 years. Compared to FIT, the competitive bidding in these auctions allows unbiased price setting, reducing regulatory intervention in the establishment of prices and resulting in greater cost efficiency for RES-E. However, since prices are set on a long-term basis, efficiency improvements cannot be integrated in PPAs and they might not reflect actual costs of RES-E after some years.

A different way of promoting green sources of energy is the creation of TGC markets. The regulator may create a demand for the Renewable Energy through the distributors' obligation to meet a specified share of green energy. These markets aim to promote green energy sources by separating electricity as a commodity (traded on the wholesale market) from the ecological attributes of electricity (avoiding CO_2 emissions, etc.), which are traded as a different product on the green certificate market. Indeed, both markets are separated but there are strong interactions between the determination of the price of the certificate, the price of the electricity and the role of regulation (Jensen and Skytte, 2002).

Although a TGC system provides less market certainty than price-based mechanisms, price fluctuations and market dynamics can be partly influenced by the design of the regime (Gan et al., 2005). Another source of evidence in favor of TGC is effectiveness in the achievement of the goal to secure a certain share of renewables in electricity consumption (Bye, 2003). Competition between producers and an increasing supply of green certificates are expected to lead to a downturn in the price of RES-E, so in this respect, the green certificate system is considered to be a cost effective way to meet the Renewable Energy target (Schaeffer et al., 1999). One more argument in favor of a TGC market is the issue of equity, defined in Bergek and Jacobsson (2010) as the fairness of the distribution of costs and benefit between different actor groups. The market decides the level of support given to renewable electricity production, so apart from guaranteeing the production of a certain quantity of RES-E, green certificates are added to the revenue that the producer can get for the electricity itself. Additionally, the introduction of market forces on the 'non-electricity' attributes of energy is supposed to bring about greater efficiency. The transition to market based solutions leads to effective competition between different forms of power from Renewable Energy sources, since producers must try to benefit from technical progress due to the pressures of bidding processes on the certificates market (Menanteau et al., 2003).

However, when designing appropriate Renewable Energy support frameworks, one of the main criticisms of TGC markets concerns the competition between renewable technologies at different stages of development.[17] On the one hand, if the certificate price tallies with the most expensive renewable technology included in the system, all technologies with lower costs would receive an extra profit (Verbruggen, 2004) and the promotion of the total renewable portfolio would be more expensive than necessary. On the other hand, if the certificate price corresponds to the moderately non-competitive technologies, one possible solution is to reserve the green market for the most mature ones (Meyer, 2003); and thus, Photovoltaics being at an earlier stage could benefit from a FIT approach, while Wind or Biomass would be ready to compete in a TGC market (Midttun and Gautesen, 2007). Moreover, instead of FIT, additional investment subsidies for developing technologies could be available, improving the economic incentives for investments. Finally, another source of criticism against TGC markets is their administrative complexity and the cost related to the support of the certificate system, since TGC have to be awarded and a market needs to be established.

All in all, current support mechanisms -FIT, Renewable Energy Auctions and TGC- exhibit both pros and cons. As a matter of fact, there is currently no general agreement on the appropriateness of the different schemes. Nevertheless existing literature supports that the type of allowance given to each renewable technology must be adapted according to their stages of maturity (Christiansen, 2001; Meyer, 2003; Jacobsson and Lauber, 2006). Technological maturity is closely related to the cost per MWh of each technology (unit cost) and the support system should be defined accordingly. Table 3.1 shows the three main categories that can be distinguished according to the maturity level.

[17]See Table 3.1 for a classification of the incentive schemes according to technological maturity

TABLE 3.1: RES classification according to technological maturity.

Category	Definition	Technologies included
1. Cost-competitive	These technologies are not eligible for policy support, since their unit cost is similar to (or even lower than) conventional sources.	This category only includes Large Hydro at the present time, which does not benefit from public incentives schemes.
2. Moderately non-competitive	These technologies are to be complemented with a relatively modest support system (e.g. TGC, FIP). The unit cost of RES-E included in this category is higher than the cost of electricity generated by some conventional sources.	Most of the current technologies could be included in this category. Such technologies may include Small Hydropower, some Biomass-based technologies and onshore Wind power.
3. Non-competitive	Those technologies that are still far from being market-ready, but have the potential to join the first category in the longer term, should be supported by incentive schemes (e.g. FIT, direct subsidies). These technologies would not survive without incentives, since the investment in R&D needed to make them competitive would never take place.	In the very beginning of RES-E deployment all technologies were ranked in this group. Nowadays, only expensive technologies and technologies in the technical development phase, such as Solar Photovoltaic or offshore Wind power technologies, are included in this category.

Source: Jansen (2003) and Ciarreta et al. (2014b).

3.2.2 Literature Review

There is a wide range of literature published on green certificates. First, focusing on European countries, some authors pose numerical models on the implementation of TGC markets in Nordic countries (Bergman and Radetzki, 2003; Bye, 2003; Nese, 2003). Second, another line of research, not aimed in this chapter, includes the interaction between TGC and Emission Trading Schemes (ETS) (Morthost, 2001; Finon and Menanteau, 2003; Jensen and Skytte, 2003; Unger and Ahlgren, 2005; Aune et al., 2012). Third, and closely related to our chapter, other authors analyze the interaction between TGC and the electricity market. Some solve partial equilibrium model under autarky (Jensen and Skytte, 2002), another group focuses on multi-country models (Amundsen and Mortensen, 2001; Morthorst, 2003; Buttler and Neuhoff, 2008) and others face the market power problem on the TGC market (Amundsen and Bergman, 2004; del Rio, 2007; Madlener et al., 2008).

Regarding the penalty function for non-compliance with the RES-E target, some authors consider the hypothesis of a variable fine as a percentage of the certificate price, for instance 200% of the market price of certificates (Jensen and Skytte, 2002); whereas others pose a fixed fine depending on the number of certificates missed (Madlener et al., 2008). In the former case, the information on the value of the penalty is not known in advance, since it depends on the certificate price, and retailers will then try to fulfill the obligation. On the contrary, in the latter case retailers are given this information in advance, so that they will take their demand decisions depending on the value of the fine. Both fix and variable penalty functions are used to establish the demand for certificates, which generally is modeled as inelastic. However, to the best of our knowledge, none of the papers has yet addressed an elastic demand for green certificates through the penalty function.

Finally, concerning the Spanish market, Linares et al. (2008) present an application of their model to the Spanish power system, observing the interactions between the electricity market, TGC market and emissions allowance market. Similarly, Fagiani et al. (2014) use Spanish data to calibrate their model to analyze the impact of carbon reduction and renewable support policies in the electricity sector. Both papers conclude that a single policy is not a cost-efficient way of achieving both a reduction of CO_2 emissions and an increase in renewable electricity generation, which are two important goals in European energy policy. However, this chapter only focuses on the RES-E promotion target, in order to obtain a good understanding of the interactions between the electricity market, the TGC market and the role of regulatory intervention in the setting for the penalty function. Policy measures aimed specifically at reducing emissions are left for further research, despite the fact that promoting RES-E indirectly leads to a decrease of emissions when green electricity replaces black electricity. Another argument to forgo emission analysis in our model is that electricity prices internalize the cost of emissions[18] and, since we focus on a one-country model and ETS are traded internationally, we consider that carbon prices would not be affected by the internal market. In any event, we will explore the effects of emissions allowances in future versions of the model.

3.3 The model

In this section, we build a model for the certificates market, the electricity market and the interaction between them. Electricity considered as a commodity is a homogenous good, independently of the energy source, and it is traded on a liberalized physical electricity market. The eco-services provided by some sources of energy are sold separately on the green certificates market or subsidized through FIT. The ecological impact of different Renewable Energy sources may be different, along with the cost associated to the electricity system management. However, we assume here for simplicity's sake that the RES-E ecological services are also a homogeneous good, ignoring the differences between technologies. The introduction of different energy sources would be straightforward.

[18]See Chen et al. (2008) for a detailed analysis of the pass-through of emission costs to consumers.

We present a two-stage model with no uncertainty. The game takes place in two stages:

- Stage 1: Electricity generators make supply decisions and retailers make demand decisions. Generators are awarded certificates depending on their green production. The wholesale market clears every period h (e.g. one hour).
- Stage 2: Production decisions taken at Stage 1 determine the amount of certificates that can be sold on the market. Retailers buy certificates to fulfill their obligations. The market for certificates clears every period H (e.g. one year), with $H > h$.

We assume that both markets work under perfect competition.[19] The TGC are issued at the end of Stage 1 to be sold at Stage 2. We solve the game using backwards induction, i.e. we first solve the market for certificates (Stage 2). Production decisions are observable at this stage.

We consider that each generator produces both renewable and non-renewable electricity and that each producer is awarded a certain amount of TGC depending on the clean electricity delivered to the network. Those TGC are assumed to have a regulator's defined life of one period, so banking is not allowed in our model and unused certificates are withdrawn from the market when the period expires.[20]

Regarding the RES-E technology mix, we assume the regulator sets a target in terms of total production of green energy, although one could also be established for each clean energy source. Some authors are in favor of a technology neutral design in order to promote competition between the certificate-eligible technologies. With a single market for all green energy sources, the market selects the technologies to achieve the target, which encourages a cost-efficient deployment of Renewable Energy sources (Nilsson and Sundqvist, 2007). On the contrary, other authors (Schmalensee, 2011) suggest that technology-specific multipliers could be used to penalize some intermittent technologies, such as Wind, given the costs they impose on the electric power system due to their intermittency or even to reward certain technologies because of the perceived external effect of induced learning-by-doing if their production is increased, such as Biomass. We present the technology neutral design and for the sake of simplicity we treat all renewables as a whole, although the analysis could be easily extended to consider several technologies.

[19] However, some authors suggest that the high concentration level in generation and the low demand elasticity may indicate the presence of market power on electricity markets (Green and Newbery, 1992; Cardell et al., 1997; Fabra and Toro, 2005; Ciarreta and Espinosa, 2010a). Similarly, other authors claim that the importance of the location of suitable sites for Wind or Hydro power plants may yield market power on the TGC market (Amundsen and Bergman, 2004). However, we leave the analysis of these markets with price-maker agents for future research.

[20] Certificates may have a longer life and there may be certificates on the market with different lifespans and different trading prices, but we ignore banking.

There are three main players in our model: the regulator, retailers (demand side), and generators (supply side); and two interacting markets (electricity and certificates). We will start by solving the TGC market.

The notation used in the model is compiled in Table B.1 in Appendix B.

3.3.1 The Tradable Green Certificates (TGC) market

3.3.1.1 Regulation on the TGC market

The TGC market should be regulated given the market failures. First, this would be to internalize the positive externalities of producing RES-E and, second, to deal with information asymmetries, since the energy attribute being sold on this market is not observable to end-use consumers. The regulator therefore certifies the resources used in the energy production process and assigns the property rights. On a TGC market, property rights are assigned to green generators, while these rights are allocated to consumers in the case of carbon pricing (e.g. ETS in Europe). In this chapter we consider that green producers receive certificates with a serial number for each green MWh produced. These certificates can then be marketed and their sale and use closely monitored.

Certificates are generally issued by government decision. We assume a one-to-one link between the number of green certificates allocated and the number of MWh produced by renewable technologies (i.e. 1 MWh = 1 certificate). The obligation to buy certificates could be transferred to the supply side (e.g. Italy until 2012) or to the demand side (e.g. retailers in the UK or end-users in Sweden). In the first case, suppliers are required to purchase certificates. Producers and importers may inject renewable electricity into the grid or purchase an equivalent number of certificates from green electricity producers. In the latter case, retailers or end-user are responsible for buying the certificates. Our model considers that the obligation to buy TGC is set for retailers, calculated on the basis of the desired share of renewable consumption. This would avoid the free-riding problem due to the public-good nature of the ecological benefit of green electricity (Menanteau et al., 2003). Relying on consumer individual choice to generate the renewable electricity demand has also been proposed as an alternative to obligatory schemes, but this option seems to have little impact on the deployment of Renewable Energy technologies (EWEA, 2004), since most consumers prefer Renewable Energy but are not willing to purchase it at higher prices (Rader and Norgaard, 1996). Moreover, we would expect the demand coming from end-use consumers to be so low that the equilibrium price would not reflect the social value of the ecological benefit of green energy. Thus, a mandatory quota of TGC for retailers may solve this market failure.

Clear consistent government policy is thus needed to set a stable green certificate system (Schaeffer et al., 1999). Minimum and maximum prices could be established in order to protect both TGC producers and consumers. Minimum values could be secured when the government itself also acts as a buyer of green certificates (e.g. the Walloon region in Belgium), whereas maximum values could be set through a penalty system for non-compliance. We will not allow the government to buy certificates and, therefore, the minimum certificate price will be zero (non-negative prices). Regarding maximum values, the regulator will set the values of the parameters in the penalty function and this sets an upper limit for the certificate price.

The penalty function maps retailers choices regarding green certificates as monetary losses resulting from deviations from the target. We model the penalty as a quadratic continuous loss function that leads to a decreasing demand for TGC. Following the literature on optimal monetary policy, the argument in our penalty function is the deviation from the policy target.[21] The penalty function for a retailer is given by the continuous function $P(x_R)$[22]:

$$P(x_R) = \begin{cases} \dfrac{f}{2}(x - x_R)^2 & \text{if } x_R \leq x \\ 0 & \text{if } x_R \geq x, \end{cases} \tag{3.1}$$

where $f > 0$ is the scale parameter of the penalty function[23], x is the retailers' obligation to purchase TGC and x_R is the amount of TGC bought by the retailer. The higher the parameter f the higher the incentives are to fulfill the objective set by the regulator.

This penalty function sets a price-cap ($\frac{f}{2}x$), since no retailer would demand green certificates at a higher price than the penalty incurred for non-compliance. Retailers not complying with the target would pay depending on the number of certificates not acquired, whereas retailers buying more than the target would neither pay for it nor receive any reward for the extra certificates acquired.

Figure 3.2 represents the shape of the quadratic penalty function (Equation (3.1)) compared to a linear penalty function. We observe that in the quadratic setting (solid) penalty levels grow more than proportionally as the deviation from the target (dotted) is higher. In that way large deviations from the target are penalized per unit more than small deviations. Furthermore, from a mathematical standpoint, the fact that the first derivative in a second-order functional form is linear gives rise to a first order condition represented by a linear function.

In short, policy makers in our TGC model set the amount of certificates that each green producer receives in relation to the proportion of green electricity produced (a one-to-one relationship

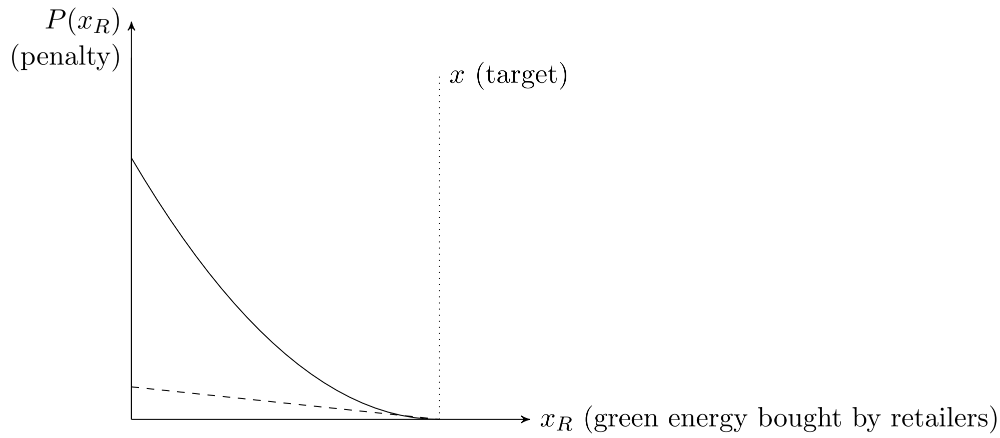
[21] The loss function for a central bank usually includes two or more targets (inflation, output fluctuations around the potential ...)

[22] All retailers face the same penalty function.

[23] Including a linear term in order to smooth out the penalty function barely changes the results. See Ciarreta et al. (2014b).

here). Their decision variables are x and f: (i) the retailers' obligation to purchase a minimum number of TGC (x, that will be stated as a quota α of retailer's sales) and (ii) the penalty to be paid by any retailer who does not meet the obligation x (parameter f).

FIGURE 3.2: Penalty function. Linear (dashed), quadratic (solid) and target (dotted).



3.3.1.2 The role of retailers on the TGC market

Two parties are involved on the demand side: the end-users of electricity and the retailers. Retailers get their margins from buying wholesale and selling to end-users. Demand for TGC comes from the retailer's obligation to pay for the environmental attributes of energy. In our analysis, electricity retailers will have an incentive to buy certificates from the producers, since they must pay a non-compliance fine when they deviate from the target x. However, they are allowed to choose the amount of TGC they want to buy on the market. Thus, when $x_R \leq x$ the optimization problem for retailers for period H is defined as follows:

$$\max_{x_R} \pi_R = \sum_{h=1}^{H} q_{R_h} \left(s - p_{e_h}\right) - x_R p_c - \frac{f}{2}(x - x_R)^2 = q_R \left(s - p_e\right) - x_R p_c - \frac{f}{2}(x - x_R)^2,$$

where $q_R = \sum_{h=1}^{H} q_{R_h}$ is the total amount of electricity bought by one retailer in period H (e.g. one year), s is the fixed price to the end-users of electricity, p_e is the price at the pool and p_c is the certificate price on the TGC market.

The elasticity of the demand for certificates will depend on the obligation x and the parameter of the penalty function f. Retailers decide x_R in the second stage and the number of TGC traded is determined endogenously.

The retailer's obligation to acquire TGC is set as a proportion of the demand for electricity in the previous period and the government target: $x = \alpha q_R$, where $0 \leq \alpha \leq 1$ is the quota of renewable electricity imposed. Hence, the optimization problem can be expressed as:

$$\max_{x_R} \pi_R = q_R\,(s - p_e) - x_R p_c - \frac{f}{2}(\alpha q_R - x_R)^2$$

Note that the price s that end-consumers pay is fixed. Likewise, the demand for electricity q_R and the selling average price p_e are given at this stage, since when the TGC market opens, the energy production decisions have already been made and the energy market has cleared. The retailer is a price-taker on the TGC market so that p_c is considered fixed in this maximization problem.

The first order condition reads:

$$\frac{\partial \pi_R}{\partial x_R} = -p_c + f(\alpha q_R - x_R) = 0$$

It follows that a retailer's demand for certificates is:

$$x_R = \begin{cases} \alpha q_R - \frac{p_c}{f} & \text{if } p_c \leq \alpha f q_R \\ 0 & \text{if } p_c \geq \alpha f q_R, \end{cases} \tag{3.2}$$

where $0 \leq \alpha \leq 1$ and $f > 0$.

The certificate system therefore is steered by the parameter of the penalty function f, but also influenced by the regulated obligation α.

Aggregate demand for TGC is the total demand for certificates in the retailing sector (K retailers) in period H:

$$X_R = \begin{cases} \alpha Q_R - \dfrac{p_c}{F} & \text{if } p_c \leq \alpha F Q_R \\ 0 & \text{if } p_c \geq \alpha F Q_R, \end{cases} \tag{3.3}$$

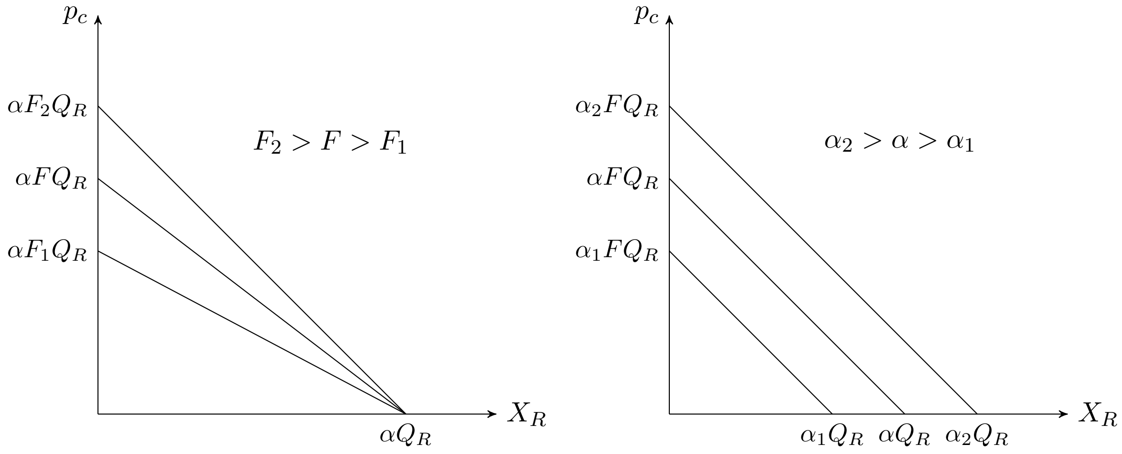
where $X_R = \sum_{k=1}^{K} x_R$ is the aggregate demand for certificates of the K retailers, $Q_R = \sum_{k=1}^{K} q_R$ is the aggregate electricity sales to the end-users and $\frac{1}{F} = \sum_{k=1}^{K} \frac{1}{f}$. Figure 3.3 plots the effect of the regulatory parameters on the demand function for certificates. In the case of the parameter of the penalty function, we observe that higher values for F shift demand upwards with a higher slope. Similarly, the parameter α shifts demand but the slope is kept constant.

Note that $x_R > x$ is never optimal, so that $x_R \leq x$ for all retailers. If $x_R = x = \alpha q_R$ for all retailers, then $p_c = 0$ from Equation (3.2), meaning that if all retailers meet the target, the certificate price will be zero.

To summarize, the aggregate retailers' demand function for TGC depends on the total amount of energy sold to the final consumer, the price of the certificates, the TGC percentage requirement α and the aggregate parameter of the penalty function F. The number of TGC that a retailer is willing to buy depends negatively on the certificate price. Aggregate demand is zero when

$p_c \geq \alpha F Q_R$, while there is a positive demand for certificates as long as $p_c < \alpha F Q_R$ holds. Furthermore, if $p_c = 0$, retailers buy the stipulated share of certificates, αQ_R, and would buy more than that only if the certificate price is negative (not allowed). Regarding the regulation parameters, since F represents the relative weight of the fine, the higher F is, the higher the retailers' demand and the higher the certificate price will be (See the left side of Figure 3.3). Similarly, high renewable quotas (i.e. high α) lead to higher prices (See the right side of Figure 3.3). The correct setting of regulation parameters by policy makers is thus important, but market forces will adjust market outcomes.

FIGURE 3.3: Role of regulation parameters (F and α) in the demand for green certificates.



3.3.1.3 The role of generators on the TGC market

Since generators hold the property rights of the renewable attribute of energy, TGC supply is determined by the optimal generators' decisions concerning the selling of green certificates. Each generator can produce both renewable and non-renewable electricity and a certain number of TGC is allocated depending on the clean electricity delivered to the network. We assume a one-to-one link between the number of green certificates allocated and the number of MWh produced by renewable technologies. Hence, a generator's supply of certificates (x_G) is constrained to its production of green electricity (q_g): $x_G \leq q_g$.

Perfect competition on the certificates market ensures that firms are not able to modify the market price by changing their own certificates production or demand, so the following identities hold: $x_G = q_g$ for each generator and $X_G = Q_g$ for the aggregate supply. That is, the aggregate supply of certificates under perfect competition is the electricity produced by green sources.

3.3.1.4 Market balance for green certificates

We use the condition of market balance for Tradable Green Certificates in order to determine the equilibrium certificate price. The total number of certificates sold has to be equal to the demand for certificates: $X_G = X_R$. From (3.3), the market balance equation for the TGC market is therefore given by:

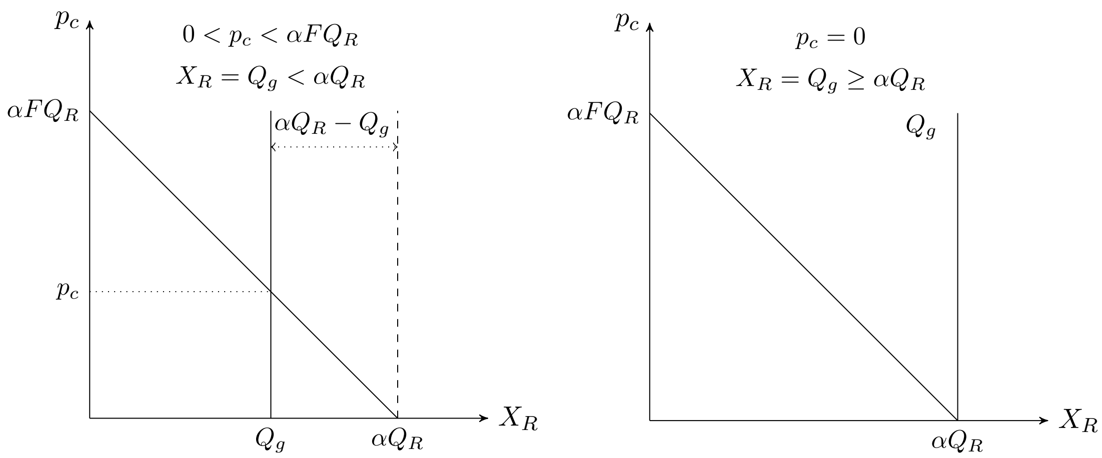
$$Q_g = \alpha Q_R - \frac{p_c}{F}$$

Hence, the equilibrium price of certificates may be written as the product of the penalty parameter F and the deviation from the target:

$$p_c^* = F \cdot (\alpha Q_R - Q_g)$$

The higher the deviation $\alpha Q_R - Q_g$, the higher the price is. With no deviation, $\alpha Q_R - Q_g = 0$, the certificate price is zero (see Figure 3.4). The price increases with the deviation from the objective and therefore provides the incentives for investment in clean energy sources.

FIGURE 3.4: Equilibrium on the certificates market.



Finally, substituting $Q_R = Q_g + Q_b$ the TGC price in equilibrium can be expressed as:

$$p_c^* = \begin{cases} F \cdot [\alpha Q_b + (\alpha - 1) Q_g] & \text{if } X^* \leq \alpha Q_R \\ 0 & \text{if } X^* \geq \alpha Q_R, \end{cases} \tag{3.4}$$

And the quantity of certificates traded in equilibrium will be:

$$X^*(p_c^*) = Q_g \tag{3.5}$$

There will be a positive demand for certificates as long as the certificate price is lower than $\alpha F Q_R$. For $p_c > 0$ retailers will deviate somewhat from the target and the higher the certificate price the higher the deviation is.

3.3.2 The electricity market

3.3.2.1 The generators' behavior on the electricity market

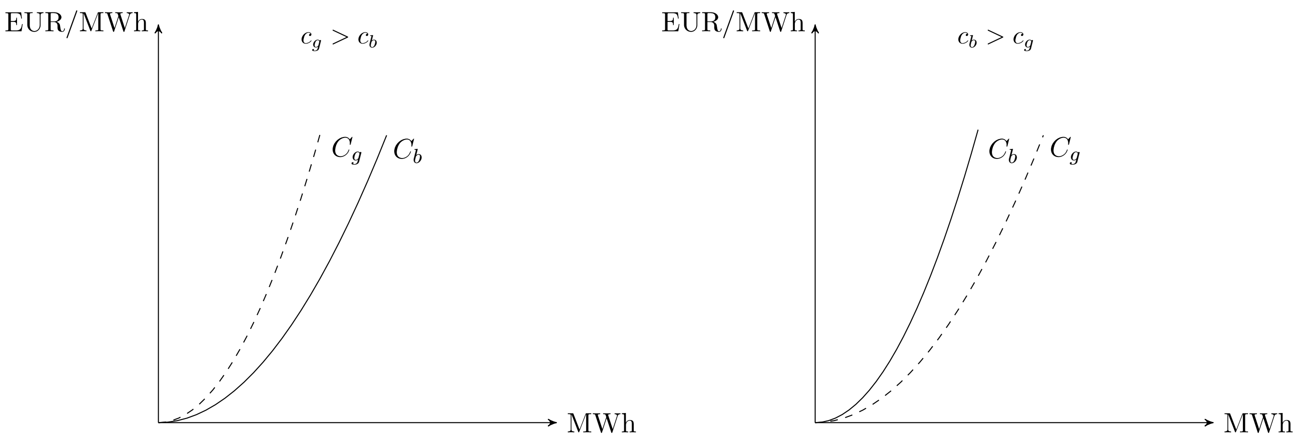
The electricity market clears on an hourly basis. Subindex h takes values from 1 to H, where H is the total number of hours in the year. We assume that each generator has renewable (green) and non-renewable (black) energy production (q_{g_h} and q_{b_h}, respectively) and that both types of production plants are necessary to satisfy the demand for energy.

Regarding costs, we assume additively separable cost functions for every hour h with respect to the quantities of conventional and Renewable Energy sources. We also assume linearly increasing marginal costs.[24] Total costs for black and green generation are respectively (see Figure 3.5):

$$\begin{aligned} C_{b_h}(q_{b_h}) &= c_{b_h} q_{b_h} + \frac{1}{2} c_h q_{b_h}^2 \\ C_{g_h}(q_{g_h}) &= c_{g_h} q_{g_h} + \frac{1}{2} c_h q_{g_h}^2, \end{aligned}$$

where c_{b_h}, c_{g_h} and c_h are the coefficients of the linear and quadratic terms in the cost functions and they specify the parameterization of the cost functions. Parameters c_{b_h} and c_{g_h} stand for unit costs at $q_{b_h} = 0$ and $q_{g_h} = 0$ for black and green electricity, respectively. Parameter c_h is non-negative ($c_h \geq 0$), which enforces convexity in the cost functions. By assuming the same parameter c_h for both cost functions, we ensure that the marginal cost curves do not cross.[25]

FIGURE 3.5: Cost functions. Green electricity (dashed), black electricity (solid).



[24]Other authors such as Baldick et al. (2004) have used similar cost functions to model electricity markets.
[25]Other authors have modeled these cost functions with two different parameters (Ciarreta et al., 2011).

We assume that there are no strict capacity constraints, but the convexity of the cost function implies that increasing production above a certain level is so costly that it amounts to a capacity constraint.

Each generator owns m plants for black energy for each green production unit. The generator decides its level of electricity supply for every hour in Stage 1. Hence, the optimization problem to be solved by each generator is:

$$\max_{q_{b_h}, q_{g_h}} \pi_{G_h}(q_{b_h}, q_{g_h}) = p_{e_h}(\sum_{j=1}^{m} q_{bj_h} + q_{g_h}) - \sum_{j=1}^{m}(c_{b_h} q_{b_h} + \frac{1}{2} c_h q_{b_h}^2) - [(c_{g_h} - p_c) q_{g_h} + \frac{1}{2} c_h q_{g_h}^2]$$

where for hour h, q_{g_h} and $\sum_{j=1}^{m} q_{b_h}$ are the quantities sold by one generator of green and black electricity, respectively; p_{e_h} is the electricity price, c_h, c_{g_h} and c_{b_h} are parameters of the cost functions and p_c is the subsidy per unit of production. If there is a market for green certificates, as it is the case here, then p_c is the certificate price; in the case of FIT, p_c would be the corresponding tariff.

The first order conditions are:

$$\frac{\partial \pi_{G_h}}{\partial q_{bj_h}} = p_{e_h} - c_{b_h} - c_h q_{bj_h} = 0 \tag{3.6}$$

$$\frac{\partial \pi_{G_h}}{\partial q_{g_h}} = p_{e_h} + p_c - c_{g_h} - c_h q_{g_h} = 0 \tag{3.7}$$

These conditions state that the marginal cost of all plants $(m + 1)$ is equal in equilibrium. Generators are assumed perfectly competitive on both markets and they produce green electricity so that marginal revenue $(p_{e_h} + p_c)$ equals marginal cost $(c_{g_h} + c_h q_{g_h})$.

For a representative producer, the supply functions of black and green energy are, respectively (the supply of black energy is the sum of the supply of the m black plants):

$$\begin{aligned} q_{b_h} &= \sum_{j=1}^{m} q_{bj_h} = \frac{m(p_{e_h} - c_{b_h})}{c_h} \\ q_{g_h} &= \frac{p_{e_h} + p_c - c_{g_h}}{c_h} \end{aligned}$$

Under a TGC system the payment received by green producers for each certificate provides incentives for green electricity in comparison with fossil fuel-based electricity. From (3.6)-(3.7): $c_{b_h} + c_h q_{b_h} = c_{g_h} + c_h q_{g_h} - p_c$, and the higher p_c, the higher q_{g_h} will be in equilibrium.

Considering N generating firms on the electricity market, the aggregate supply for every hour h is:

$$\begin{aligned}
Q_{b_h} &= \sum_{i=1}^{N} \frac{m(p_{e_h} - c_{b_h})}{c_h} = \frac{Nm(p_{e_h} - c_{b_h})}{c_h} \\
Q_{g_h} &= \sum_{i=1}^{N} \frac{p_{e_h} + p_c - c_{g_h}}{c_h} = \frac{N(p_{e_h} + p_c - c_{g_h})}{c_h} \\
Q_{G_h} &= Q_{b_h} + Q_{g_h} = \frac{N[(m+1)p_{e_h} + p_c - (mc_{b_h} + c_{g_h})]}{c_h},
\end{aligned}$$

where annual aggregate quantities are $Q_b = \sum_{h=1}^{H} Q_{b_h}$, $Q_g = \sum_{h=1}^{H} Q_{g_h}$ and $Q_G = \sum_{h=1}^{H} Q_{G_h}$. The slope of the inverse supply function of hour h is $\frac{c_h}{(m+1)N}$.

We assumed that $c_h > 0$. For a linear cost function, $c_h = 0$, we would have that $p_{e_h} = c_{b_h} = c_{g_h} - p_c$.

3.3.2.2 The retailers' behavior on the electricity market

For the final consumers we assume a linear demand function[26] for electricity with parameters a_h ($a_h > 0$) and b_h ($b_h \geq 0$) with $h = 1, 2, \ldots, H$:

$$Q_{R_h} = a_h - b_h p_{e_h}$$

We will denote annual demand as $Q_R = \sum_{h=1}^{H} Q_{R_h}$.

3.3.2.3 Market balance for electricity

In equilibrium, total supply of electricity for every hour h has to be equal to the demand for electricity:

$$Q_{G_h} = Q_{b_h} + Q_{g_h} = Q_{R_h} = Q_h$$

And, thus, the equilibrium electricity price for every hour h is:

$$p^*_{e_h}(p_c) = \frac{a_h c_h + Nmc_{b_h} + Nc_{g_h} - Np_c}{(m+1)N + b_h c_h} \tag{3.8}$$

This result shows that there is a negative relationship between the electricity price and the subsidy or certificate price: the higher the expected certificate price, the lower the electricity price.

[26]Other authors such as Newbery (1998) or Green (1999) have used similar demand functions to model electricity markets.

Similarly, the hourly quantity of electricity in equilibrium is as follows:

$$\begin{aligned}
Q^*_{b_h}(p^*_{e_h}) &= \frac{Nm(p^*_{e_h} - c_{b_h})}{c_h} \\
Q^*_{g_h}(p^*_{e_h}) &= \frac{N(p^*_{e_h} + p_c - c_{g_h})}{c_h} \\
Q^*_h(p^*_{e_h}) &= Q^*_{b_h}(p_c) + Q^*_{g_h}(p_c) = \frac{N[(m+1)p^*_{e_h} + p_c - (mc_{b_h} + c_{g_h})]}{c_h}
\end{aligned}$$

Inserting (3.8) into the hourly quantity functions yields:

$$\begin{aligned}
Q^*_{b_h}(p_c) &= \frac{Nm[a_hc_h - (N + b_hc_h)c_{b_h} + Nc_{g_h} - Np_c]}{c_h[(m+1)N + b_hc_h]} \\
Q^*_{g_h}(p_c) &= \frac{N[a_hc_h + Nmc_{b_h} - (Nm + b_hc_h)c_{g_h} + (Nm + b_hc_h)p_c]}{c_h[(m+1)N + b_hc_h]} \\
Q^*_h(p_c) &= Q^*_{b_h}(p_c) + Q^*_{g_h}(p_c) = \frac{N[(m+1)a_h - b_h(mc_{b_h} + c_{g_h}) + b_hp_c]}{(m+1)N + b_hc_h}
\end{aligned}$$

Annual quantities as a function of the certificate price are then:

$$Q^*_b(p_c) = \sum_{h=1}^{H} \frac{Nm[a_hc_h - (N + b_hc_h)c_{b_h} + Nc_{g_h} - Np_c]}{c_h[(m+1)N + b_hc_h]} \tag{3.9}$$

$$Q^*_g(p_c) = \sum_{h=1}^{H} \frac{N[a_hc_h + Nmc_{b_h} - (Nm + b_hc_h)c_{g_h} + (Nm + b_hc_h)p_c]}{c_h[(m+1)N + b_hc_h]} \tag{3.10}$$

$$Q^*(p_c) = \sum_{h=1}^{H} \frac{N[(m+1)a_h - b_h(mc_{b_h} + c_{g_h}) + b_hp_c]}{(m+1)N + b_hc_h} \tag{3.11}$$

Equations (3.9) to (3.11) show that the subsidy or price of certificates increases the production of green electricity and decreases the production of black electricity. However, this effect is stronger in the green production and, hence, the total production of electricity is positively affected by the price of certificates, with a greater influence being shown as parameter b_h of the demand function rises. As expected, the supply of non-renewable electricity is positively affected by the cost parameter of Renewable Energy, whereas the supply of green electricity is increased by the cost parameter of black production. Both supplies are negatively affected by their own generation costs.

3.3.3 Equilibrium on the electricity market and the green certificates market

As already stated, the game is played sequentially and agents are forward looking, so we proceed using backward induction. Electricity market first clears on an hourly basis and the TGC market second on an annual basis. We thus start from the demand for certificates in Equation (3.3), determined in Stage 2, and we substitute the expression for the equilibrium quantity of electricity (3.11). Since $Q = Q_R = Q_G = Q_b + Q_g$, from (3.3), the annual demand for certificates can be expressed in terms of the certificate price as:

$$X_R(p_c) = \alpha Q_R - \tfrac{p_c}{F} = \textstyle\sum_{h=1}^{H} \frac{F \cdot H \cdot N \cdot \alpha[(m+1)a_h - b_h(mc_{b_h} + c_{g_h})] - p_c[(m+1)N + b_h(c_h - F \cdot H \cdot N \cdot \alpha)]}{FH[(m+1)N + b_h c_h]} \tag{3.12}$$

Additionally, we get that $X_R^*(p_c^*) = Q_g^*(p_c^*)$ from the equilibrium of the TGC market (3.5), so using (3.10) and (3.12) we obtain the expression for the certificate price that generators anticipate in equilibrium (Equation (3.13)).

$$p_c^* = F \cdot H \cdot N \frac{\sum_{h=1}^{H} \dfrac{a_h c_h[(m+1)\alpha - 1] - (N + b_h c_h \alpha) m c_{b_h} + [Nm + b_h c_h(1-\alpha)] c_{g_h}}{c_h[(m+1)N + b_h c_h]}}{\sum_{h=1}^{H} \dfrac{F \cdot H \cdot N[Nm + b_h c_h(1-\alpha)] + c_h[(m+1)N + b_h c_h]}{c_h[(m+1)N + b_h c_h]}} \tag{3.13}$$

Any decrease in the costs of renewable electricity c_{g_h} decreases the equilibrium certificate price. Therefore, any efficiency improvement in the production of RES-E would have the effect of decreasing the price of the certificates. This result is relevant because, even if the regulator were not aware of the efficiency gain, the market would provide the right signals and decrease the subsidy for Renewable Energy. This is an advantage of TGC over FIT.

We have identified an important advantage of a market mechanism over a fixed subsidy. Even if the regulator could change the FIT in every period, she may not readily observe changes in the costs or demand parameters (c_{b_h}, c_{g_h}, c_h, a_h, b_h) so that the task of setting the right tariffs may become impossible. Furthermore, there are regulatory delays and even with perfect observability of the cost parameters, it would be difficult to adjust the subsidy to market conditions at the right pace.

The following two sections present an application using data from the Spanish electricity system. When we implement our model with Spanish data we argue that a regulatory system based on TGC would have reacted to market changes while the FIT incentive scheme did not.[27] In order to measure how important this TGC advantage is, we compare the actual evolution of the electricity market under FIT to a counterfactual electricity market under TGC. We first calibrate the model to obtain cost (c, c_g and c_b) and demand parameters (a and b) to build the

[27] For the sake of simplicity we call it the FIT incentive system, but we are actually considering the combined system of tariffs and premiums.

counterfactual, then we set the incentives under TGC equal to those that were in place for a given year under FIT ($p_c = p_{FIT}$) and derive the relevant regulatory parameters (α and F).

3.4 An empirical application

In this section we calibrate our theoretical TGC model using data from the Spanish electricity system for the period 2008-2013. This procedure provides equilibrium values equivalent to the ones that were in place under the FIT scheme. Before conducting the calibration exercise, we start by describing some key aspect of the Spanish electricity regulation. We then calculate the values for the market parameters: demand and cost parameters, specifically. Finally, we calibrate the regulatory parameters, which are selected so that the equilibrium certificate prices in our model replicate actual FIT. This will be the starting point for the simulations using counterfactual setups in Section 3.5.

3.4.1 The Spanish electricity system

In a scenario of renewable expansion in Europe, Spain reached a 33% of the electricity generated from RES in 2010 (IDAE, 2012) and forecasts point towards 41% by 2020 (Eurostat, 2012; EWEA, 2011). Moreover, Spain boasts important levels of renewable installed capacity, with a 34% of RES and cogeneration out of the total installed capacity in 2010 and having reached a 39% in 2013 (CNMC, 2014a). The question is at what cost?

The financial burden due to the Spanish incentive scheme of combined FIT and FIP, aimed at RES-E and cogeneration, grew to unsustainable levels and from 2010 onwards, market savings due to the introduction of RES-E were not able to compensate for the economic costs on consumers derived from the incentive scheme (Ciarreta et al., 2014a). Another illustrative indicator is the deficit of regulated activities, which added up to nearly 24,500 million euro in 2013 (CNMC, 2013b), from which more than 9,000 million were driven by the incentives for RES (CNMC, 2013a).[28] In this context, the Spanish Government abolished the FIP (Royal Decree-Law 2/2013) and FIT (Royal Decree-Law 9/2013) combined system in 2013 and passed Royal Decree 413/2014 in 2014, which established a new incentive scheme based on a fixed rate of return on investment. These measures lowered significantly the economic incentives for RES-E and cogeneration, threatening the survival of some facilities that were already producing (COM(2014) 410 final). Furthermore, this situation demonstrated that the choice of the best instrument is extremely difficult for policy makers, and that the complexity associated with estimating the optimal level of support is even higher.

[28] In 2014 the figure was over 7,000 million euro (CNMC, 2014b) and in May 2015 (last available data) it was close to 2,200 million euro (CNMC, 2015b).

Under these circumstances, Spain is a good country to apply our model and observe if TGC could have outperformed the FIT system in terms of the cost of reaching the RES objectives. First, a fixed FIT system resulted in huge costs for consumers, and the new support mechanism based on a fixed rate of return on investment raises doubts regarding the continuity of some RES facilities. Second, there have been considerable market changes and renewable technologies are nowadays at a quite mature stage. With investment costs dropping significantly in the last few years[29], RES do not currently need strong incentive schemes to survive, although a certain level of support may still be required. Finally, Spain is almost an energy island in terms of import/exports (5% of total consumption) and so it is a good example for a model under autarky.

3.4.2 Calibration of the market parameters

We take actual values for the hourly electricity price and the quantity of energy traded published by the market operator (OMIE). We only consider the day ahead market and not the final electricity price, which also incorporates intraday markets, restrictions and ancillary services. The day-ahead market includes most of the information of the Spanish electricity market, since it comprises about 70% of the transactions, and it accounts for more than the 80% of the final electricity price (Ciarreta et al., 2014a).

Concerning the demand parameters for every hour, we fit a linear aggregate demand function $Q_h = a_h - b_h p_{e_h}$ to actual data, obtaining estimates for the parameters a_h and b_h used in the model. With regard to electricity supply, we assume that producers behave competitively, so they bid at their marginal cost. Therefore, the aggregate marginal cost (MC) function $MC(Q_h) = \frac{c_{b_h}+c_{g_h}}{m+1} + \frac{c_h}{(m+1)N}Q_h$ is the aggregate supply curve in our model. Using OLS we estimate hourly values for the intercept $\frac{c_{b_h}+c_{g_h}}{m+1}$ and the slope $\frac{c_h}{(m+1)N}$ of the supply function.

In order to check if our linear estimates for demand and supply curves fit actual data, we build a series of estimated equilibrium prices from the intersection of our estimated demand and supply curves and we compare them with actual prices published by the market operator. For the period 2008-2013, Figure 3.6 reports this comparison of actual and estimated electricity prices. On the left, Figure 3.6a represents the mean values and the 95% confidence interval of monthly electricity prices of both series (actual as a solid line and estimated as a dashed line). On the right, Figure 3.6b shows the distribution function of hourly actual prices (solid) and the distribution of hourly estimated prices (dashed). In both figures we observe that estimated prices are slightly higher than actual prices (on average 2.89%[30]). Additionally, when we carry out the

[29] For a detailed analysis of the economics of Photovoltaics and the change in their costs see Bazilian et al. (2013).

[30] Higher deviations in 2011 and 2013 and lower deviations in 2008 and 2012: -0.92% in 2008, 2.31% in 2009, 2.22% in 2010, 9.42% in 2011, -0.98% in 2012 and 5.30% in 2013.

Kolmogorov-Smirnov equality-of-distribution test[31], we check that both series are statistically different at a 1% level. These deviations between the two distributions are mainly due to the fact that there is concavity in the supply curve around equilibrium and the linear adjustment determines a higher price.

Taking the linear approximation as valid, despite the small deviations observed in the equilibrium prices, we assume that the slope of the aggregate marginal cost function is the slope of the hourly aggregate inverse supply curve $\frac{c_h}{(m+1)N}$, so the parameter of the individual cost functions for black and green electricity (c_h) is the slope of the aggregate supply function multiplied by $(m+1)N$. To derive the individual parameters of the renewable (c_{g_h}) and non-renewable (c_{b_h}) cost functions, we apply the equilibrium condition marginal revenue (price) equals marginal cost for every hour of the year.[32]

From Equation (3.6):

$$\sum_1^N \sum_1^m (p_{e_h} - c_{b_h} - c_h q_{b_h}) = 0$$
$$Nmp_{e_h} - Nmc_{b_h} - c_h \sum_1^N \sum_1^m q_{b_h} = 0$$
$$p_{e_h} = c_{b_h} + \frac{c_h}{Nm} Q_{b_h}$$

This relationship provides hourly intercepts of the marginal cost function of black electricity.

Similarly, from the expression $p_{e_h} + p_{FIT} = c_{g_h} + \frac{c_h}{N} Q_{g_h}$, where the subsidy is now the feed-in tariff p_{FIT}, we get hourly parameters c_{g_h}. The average unit premium p_{FIT} in EUR/MWh, is computed using data from the National Energy Commission (CNMC) as the annual incentive payment in EUR, including both FIT and FIP, over the energy in MWh eligible to receive incentives.

Concerning the multiplier of non-renewable plants, m, we have computed this value on an annual basis as the quotient between total non-renewable and renewable production: $m = \frac{\sum_{h=1}^H Q_{b_h}}{\sum_{h=1}^H Q_{g_h}}$. Using market data from OMIE we observe that in 2008 the production of black plants was four times higher than the capacity of green plants ($m = 4$), whereas this relationship was 3 to 1 for the rest of the period. This is consistent with the Spanish regulation aimed at supporting Renewable Energy passed in mid 2007, which led to a greater renewable production from 2009 onwards, when plants benefiting from the subsidies could start working.

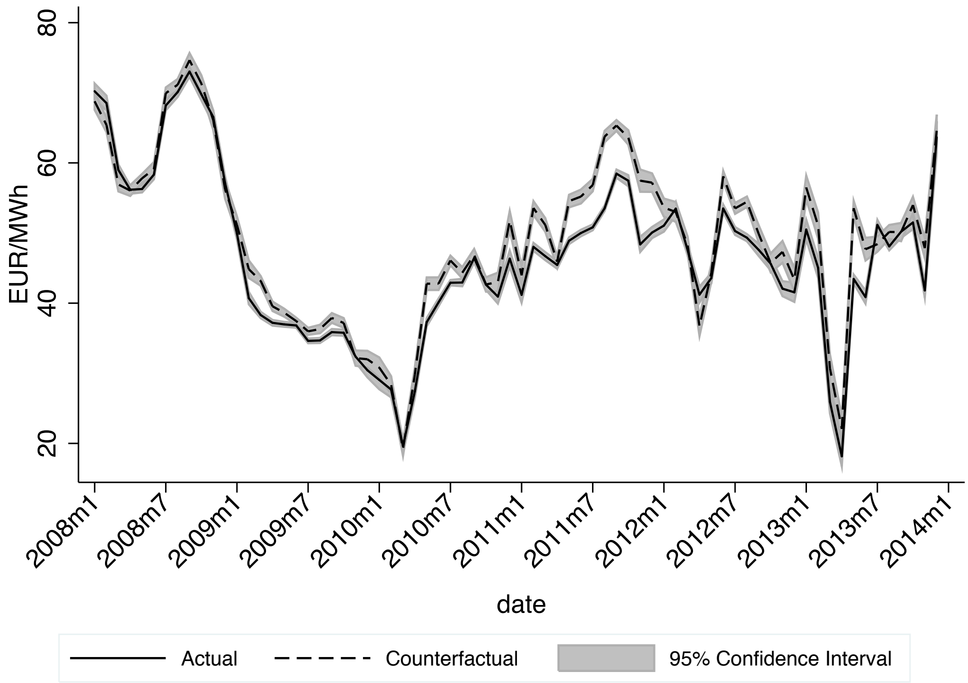
Finally, the model is not sensitive to the number of firms on the market. We present the simulation results using the value $N = 50$, but we tested for different values from 5 to 100 and we observed no change on the market outcomes.

[31] We use the Skewness and Kurtosis test for normality and we observe that both price series are not normal, so we have to use a non-parametric test for the equality of distribution.

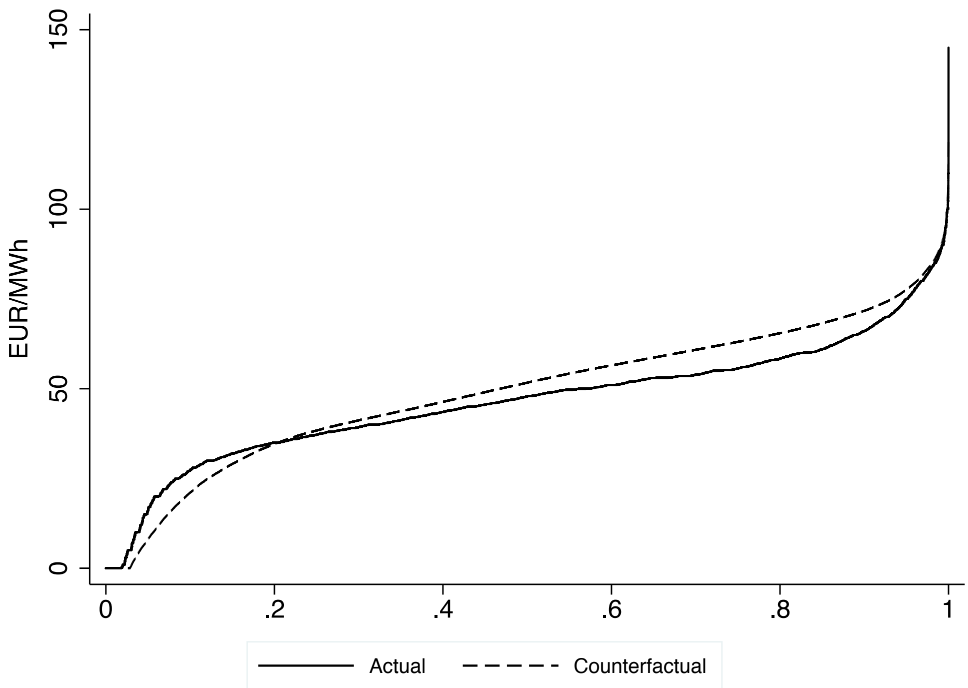
[32] To derive one of the two parameters we could also have used the intercept of the linear supply curve which should equal $\frac{c_h}{(m+1)N}$, but since renewable producers bid at the pool at zero prices (which would lead to $c_{g_h} = 0$), we decided not to relate the intercept of the supply curve to renewable costs.

FIGURE 3.6: Actual vs. estimated electricity price. Period 2008-2013

(A) Monthly electricity price. 95% Confidence Interval.



(B) Hourly electricity price. Distribution function.



Source: Own elaboration based on data from OMIE (2015b).

3.4.3 Calibration of the regulatory parameters

Once we have assigned numerical values to the demand and cost parameters, we carry out a calibration exercise for the regulatory parameters F and α. The value of F and α should match the regulatory objectives concerning green energy. Since those objectives are not readily observable, we calibrate the value of the instruments F and α to be compatible with the regulator's goals being achieved in terms of the incentives provided for a given year in the period 2008-2013. To this end, we solve for α in the equation of the certificate price (Equation 3.13), we substitute p_c for the price of the FIT, which is provided by the CNMC, and we obtain Equation (3.14).

$$\alpha = \frac{\sum_{h=1}^{H} \frac{\frac{p_{FIT}}{F \cdot H \cdot N}\{F \cdot H \cdot N(Nm + b_h c_h) + c_h[(m+1)N + b_h c_h]\} + a_h c_h + c_{b_h} Nm - c_{g_h}(Nm + b_h c_h)}{c_h[(m+1)N + b_h c_h]}}{\sum_{h=1}^{H} \frac{a_h c_h (m+1) - b_h c_h (m c_{b_h} + c_{g_h} - p_{FIT})}{c_h[(m+1)N + b_h c_h]}} \tag{3.14}$$

We then solve Equation (3.14) using the demand and cost parameters computed in Section 3.4.2 for different values of F in the range $(0,\ 10^{-4}]$. Table 3.2 shows the values of F and α that achieve an equilibrium certificate price equal to the green energy subsidy in the period 2008-2013, which for F is in the range $[10^{-6},\ 10^{-4}]$.

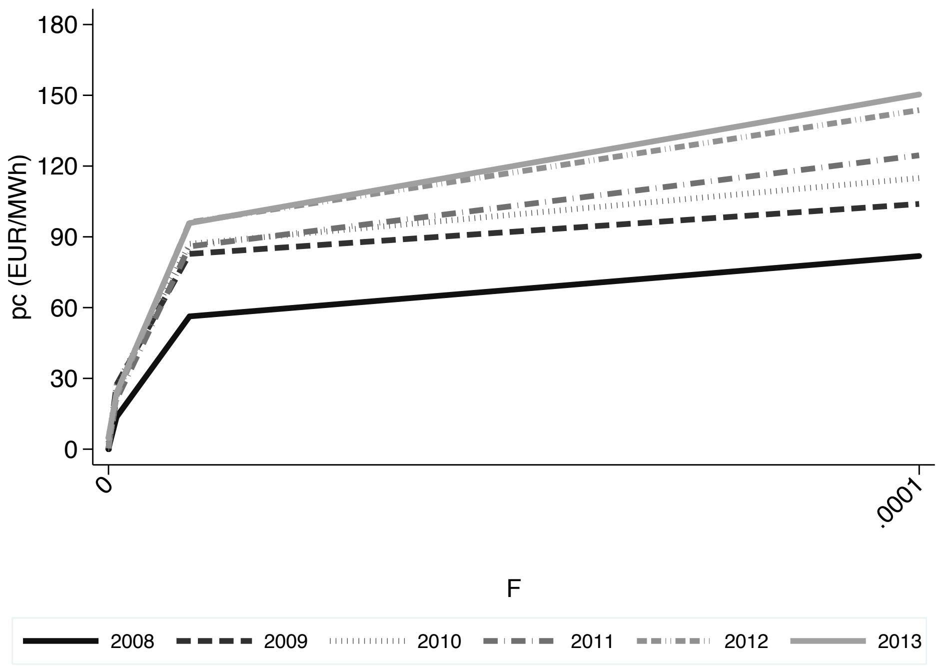
Values for F lower than $2 \cdot 10^{-6}$ require $\alpha > 1$ in order to get certificate prices that replicates actual FIT (recall that $\alpha \in [0, 1]$), and values for F higher than $4 \cdot 10^{-4}$ yield certificate prices equal to zero ($p_c \neq p_{FIT}$), due to the fact that the penalty is high enough to induce the purchase of all certificates. Therefore, any combination of F and α in Table 3.2 is suitable, since they all fulfill our calibration condition $p_c = p_{FIT}$ with $\alpha \in [0, 1]$. From now on we will work with $F = 7 \cdot 10^{-6}$ and the corresponding α for every year (highlighted in black in Table 3.2), but any of the other combinations would lead to the same result.

We have calibrated the regulatory parameters that provide a market for green certificates with the same incentives as a FIT system. Now we observe how certificate prices react to changes in these parameters F and α. Both Figures 3.7a and 3.7b represent the effect of the regulatory parameter F on the certificate price for the period 2008-2013 using the values for α that appear in bold in Table 3.2, the difference is the scale of the x-axis.

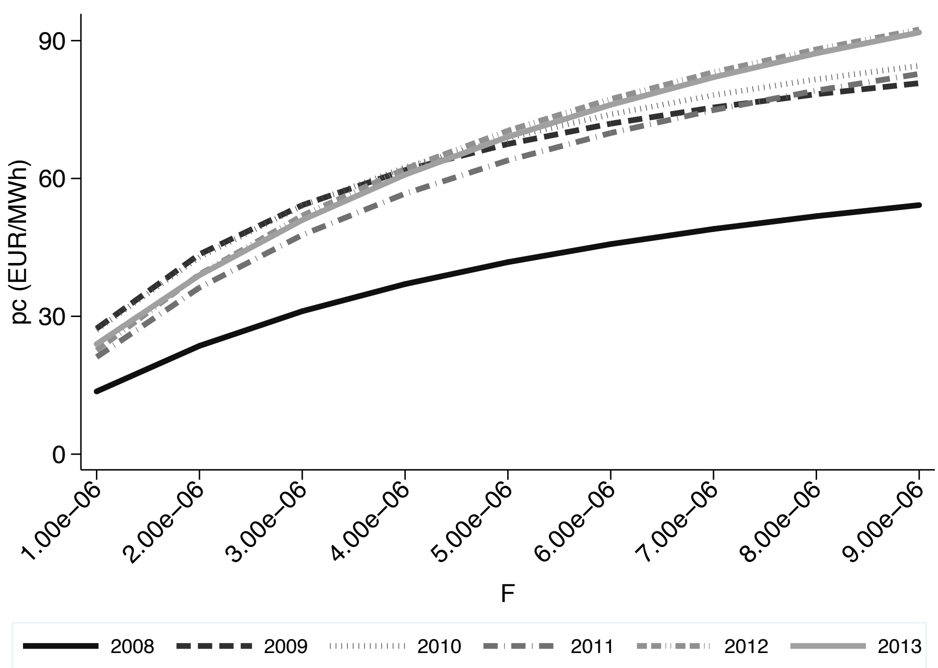
In Figure 3.7a we represent the whole spectrum of valid values for F, whereas Figure 3.7b highlights the range of values for F that induce a change in p_c that lays close to the value of the FIT. Figure 3.7a shows that the choice of the parameter F may affect the model substantially, considering that retailers decide the amount of certificates to buy depending on the relationship between the certificate price and the penalty. On the one hand, very low values for F ($F < 10^{-11}$) lead to no trade of certificates, since retailers prefer to pay the penalty, which is low, rather than buying certificates. On the other hand, there is a threshold value ($F > 10^{-4}$) for which the certificate price does not increase anymore with F. Intermediate values make retailers

FIGURE 3.7: Evolution of the certificate price with regulatory parameter F; α fixed.

(A) Sensitivity of p_c to parameter F from 0 to $9 \cdot 10^{-4}$.



(B) Sensitivity of p_c to parameter F from $1 \cdot 10^{-6}$ to $9 \cdot 10^{-6}$.



Source: Own elaboration based on data from OMIE (2015b) (electricity market data) and CNMC (2014a) (incentives).

TABLE 3.2: Calibration of the regulatory parameters F and α.

F	α_{2008}	α_{2009}	α_{2010}	α_{2011}	α_{2012}	α_{2013}
$2 \cdot 10^{-6}$	0.39134	0.57597	0.67226	0.71394	0.77554	0.80480
$3 \cdot 10^{-6}$	0.35560	0.51565	0.60630	0.64701	0.70063	0.73123
$4 \cdot 10^{-6}$	0.33774	0.48549	0.57333	0.61355	0.66318	0.69444
$5 \cdot 10^{-6}$	0.32701	0.46739	0.55354	0.59347	0.64070	0.67237
$6 \cdot 10^{-6}$	0.31987	0.45533	0.54035	0.58008	0.62572	0.65766
$\mathbf{7 \cdot 10^{-6}}$	**0.31476**	**0.44671**	**0.53092**	**0.57052**	**0.61502**	**0.64715**
$8 \cdot 10^{-6}$	0.31093	0.44025	0.52386	0.56335	0.60699	0.63927
$9 \cdot 10^{-6}$	0.30795	0.43522	0.51836	0.55777	0.60075	0.63314
10^{-5}	0.30557	0.43120	0.51396	0.55331	0.59576	0.62823
$2 \cdot 10^{-5}$	0.29485	0.41310	0.49418	0.53323	0.57328	0.60616
$3 \cdot 10^{-5}$	0.29128	0.40707	0.48758	0.52654	0.56579	0.59880
$4 \cdot 10^{-5}$	0.28949	0.40405	0.48428	0.52319	0.56205	0.59513
$5 \cdot 10^{-5}$	0.28842	0.40224	0.48231	0.52118	0.55980	0.59292
$6 \cdot 10^{-5}$	0.28770	0.40104	0.48099	0.51984	0.55830	0.59145
$7 \cdot 10^{-5}$	0.28719	0.40018	0.48004	0.51889	0.55723	0.59040
$8 \cdot 10^{-5}$	0.28681	0.39953	0.47934	0.51817	0.55643	0.58961
$9 \cdot 10^{-5}$	0.28651	0.39903	0.47879	0.51761	0.55580	0.58899
10^{-4}	0.28627	0.39862	0.47835	0.51717	0.55530	0.58850
$2 \cdot 10^{-4}$	0.28520	0.39682	0.47637	0.51516	0.55306	0.58630
$3 \cdot 10^{-4}$	0.28484	0.39621	0.47571	0.51449	0.55231	0.58556
$4 \cdot 10^{-4}$	0.28467	0.39591	0.47538	0.51415	0.55193	0.58519

Source: Own elaboration based on data from OMIE (2015b) (electricity market data) and CNMC (2014a) (incentives).

decide how many certificates to buy in order to pay the lowest fine possible, and it is in this range where our parameter F will lay. This range is represented in Figure 3.7b for the values of α selected in bold in Table 3.2, and it fluctuates from $F = 1 \cdot 10^{-6}$ to $F = 9 \cdot 10^{-6}$, leading to certificate prices from 30 EUR/MWh up to 90 EUR/MWh.

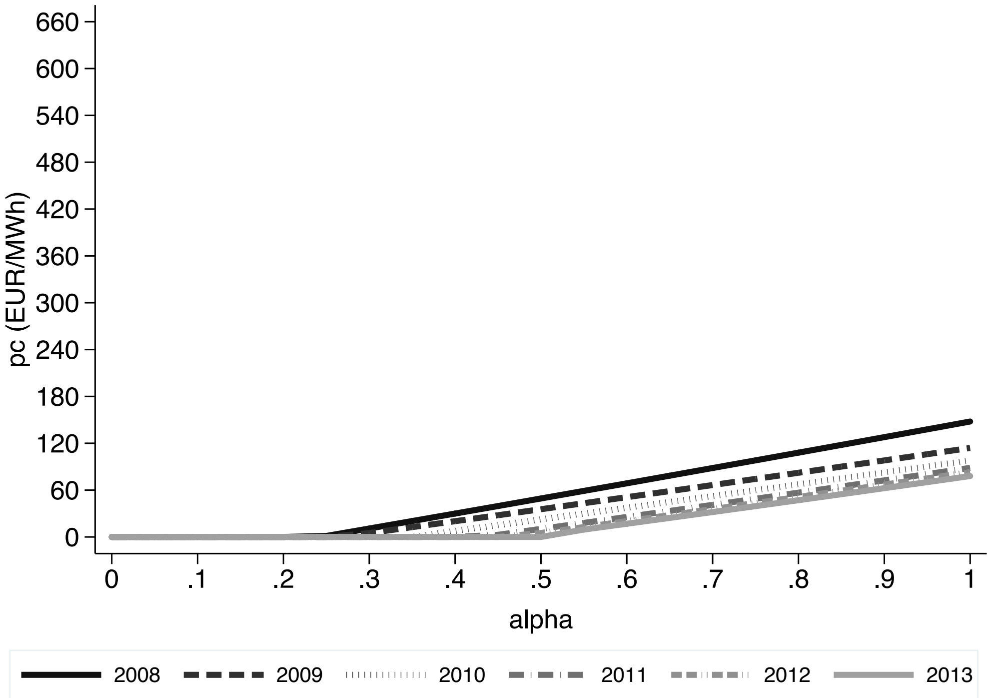
Similarly, Figure 3.8 also shows that there is a positive relationship between the target of renewable electricity α and the certificate price. If the target is set too low, no RES-E is produced and firms prefer to pay the full penalty. In this case, the certificate price is zero. As the target increases, certificate prices shift to higher values. Concerning the combined effect of F and α, we observe that certificate prices experience sharper increments with α when F is higher.

3.4.4 Fit to actual data

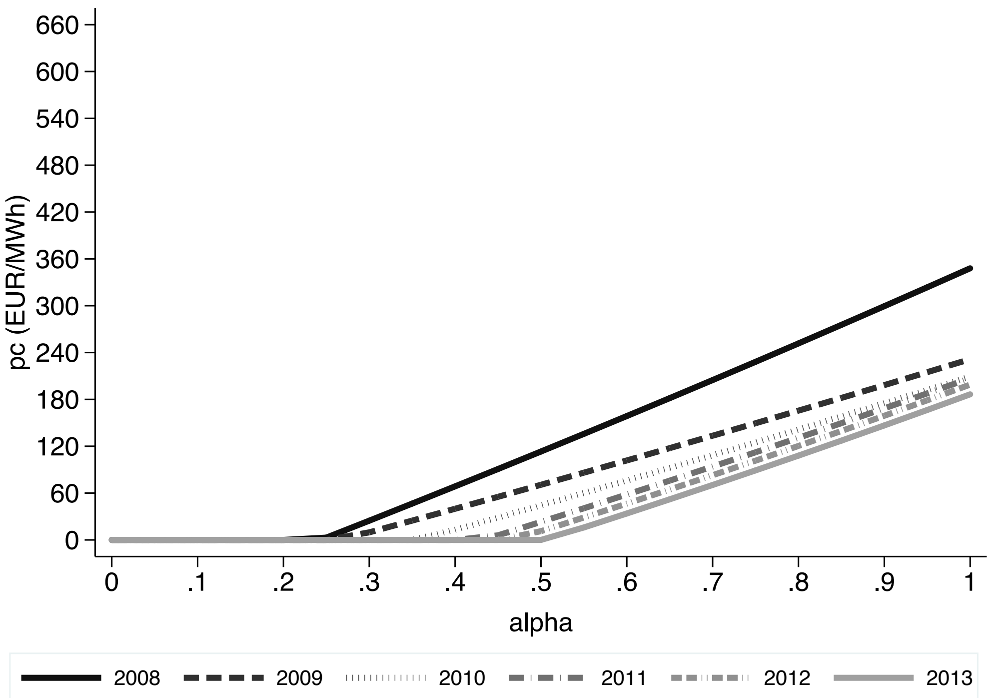
A summary of the annual parameters of the model is presented in Table 3.3. This table sets out the values computed using the methodology of Sections 3.4.2 and 3.4.3. Since the TGC market clears on an annual basis, certificate prices are equivalent to the annual average unit premium,

FIGURE 3.8: Evolution of the certificate price with regulatory parameter α; F fixed.

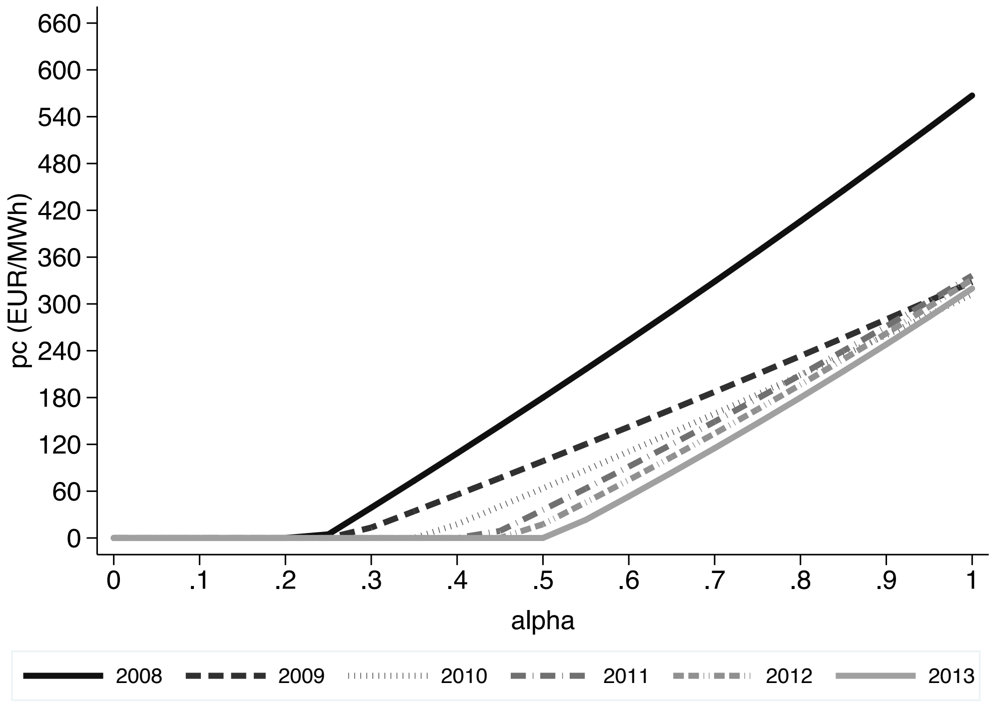
(A) Sensitivity of p_c to parameter α, $F = 1 \cdot 10^{-6}$.



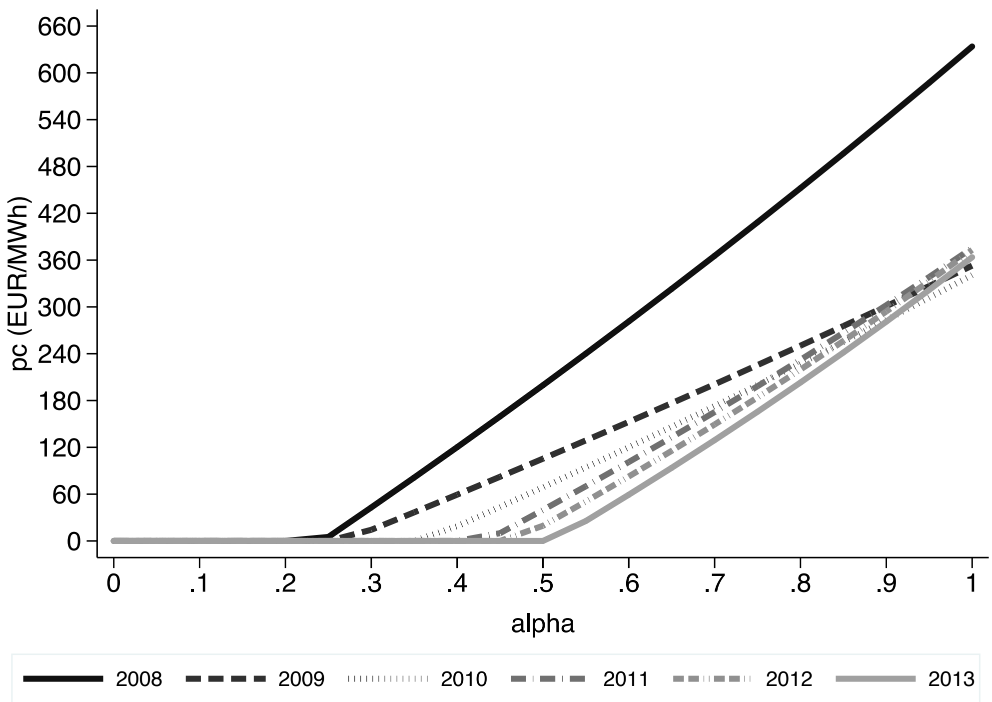
(B) Sensitivity of p_c to parameter α, $F = 3 \cdot 10^{-6}$.



(c) Sensitivity of p_c to parameter α, $F = 7 \cdot 10^{-6}$.



(d) Sensitivity of p_c to parameter α, $F = 9 \cdot 10^{-6}$.



Source: Own elaboration based on data from OMIE (2015b) (electricity market data) and CNMC (2014a) (incentives).

which is computed using data from the Spanish regulator as the annual incentive payment in EUR, including both FIT and FIP, over the energy in MWh eligible to receive incentives. In our model, certificates are issued to the technologies under the so called Special Regime (SR), which included RES and cogeneration. Considering that the Spanish electricity market clears on an hourly basis, the calibration of the market parameters has been performed for every hour; however, for the sake of better understanding we provide annual averages here. We compute these values as the annual mean of demand and cost parameters: $a = \frac{\sum_{h=1}^{H} a_h}{H}$, $b = \frac{\sum_{h=1}^{H} b_h}{H}$, $c = \frac{\sum_{h=1}^{H} c_h}{H}$, $c_b = \frac{\sum_{h=1}^{H} c_{b_h}}{H}$ and $c_g = \frac{\sum_{h=1}^{H} c_{g_h}}{H}$.

Table 3.3: Summary of annual parameters of the model.

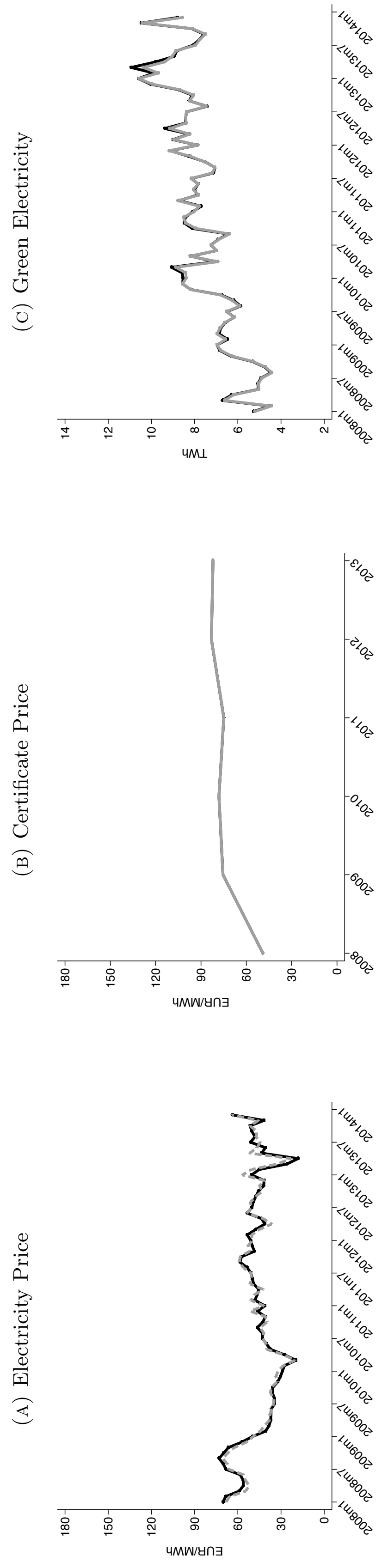
	2008	**2009**	2010	2011	2012	2013
Demand parameters:						
a	27,909.45	**24,827.85**	23,549.48	23,372.35	23,491.17	24,034.22
b	30.03	**27.59**	30.21	40.96	52.52	55.13
Cost parameters:						
c	2.0461	**1.1789**	1.6265	2.0605	2.054	2.9226
c_b	-117.29	**-64.61**	-73.85	-68.2	-70.29	-100.17
c_g	-195.29	**-112.94**	-234.88	-320.8	-340.61	-602.25
Regulatory parameters:						
F	0.000007	**0.000007**	0.000007	0.000007	0.000007	0.000007
α	0.31476	**0.44671**	0.53092	0.57052	0.61502	0.64717
Others:						
N	50	**50**	50	50	50	50
m	4	**3**	3	3	3	3
H	8,784	**8,760**	8,760	8,760	8,784	8,760
p_{FIT}	49.01	**75.46**	78.13	74.89	83.12	82.04

Source: Own elaboration based on data from OMIE (2015b) (electricity market data) and CNMC (2014a) (incentives).

Introducing these parameters in our model we obtain the results of a TGC market equivalent to a market situation with FIT and FIP. Figure 3.8 shows the time series of monthly market outcomes, including electricity prices and RES quantities; and annual certificate prices. Comparing actual (black) and simulated (gray) values, we observe that our model under perfect competition adjusts market outcomes and all time series are close to actual values for the whole period (the black and grey lines overlap).

Additionally, Table 3.4 shows the market outcomes that our model provides when it is calibrated in order to replicate the system of FIT that was in force during the period 2008-2013. We observe that certificate prices match the tariffs and premiums for every year, and that the shares of RES in the simulated electricity markets are very close to actual shares.

Figure 3.8: Market data (black) vs. Model results (gray) with annual parameters.



Source: Own elaboration based on data from OMIE (2015b) (electricity market data) and CNMC (2014a) (incentives).

TABLE 3.4: Model calibration.

year	α	Q_g %	$\hat{Q}_g$ %	Q_g TWh	$\hat{Q}_g$ TWh	Q TWh	$\hat{Q}$ TWh	p_e EUR/MWh	$\hat{p}_e$ EUR/MWh	p_{FIT} EUR/MWh	$\hat{p}_c$ EUR/MWh
2008	0.31476	28.3	28.4	65.52	64.94	231.48	228.57	64.43	61.55	49.01	49.01
2009	0.44671	39.7	39.5	81.92	82.34	206.42	208.38	36.96	38.16	75.46	75.46
2010	0.53092	47.9	47.5	94.01	93.19	196.35	196.11	37.01	37.59	78.13	78.13
2011	0.57052	51.6	51.3	95.48	95.62	185.1	186.35	49.93	51.20	74.89	74.89
2012	0.61502	55.1	55.1	102.28	101.75	185.77	184.81	47.23	46.39	83.12	83.12
2013	0.64717	58.9	57.9	109.82	108.27	186.59	187.1	44.26	46.78	82.04	82.04

Source: Own elaboration based on data from OMIE (2015b) (electricity market data) and CNMC (2014a) (incentives).

3.5 Results

In this section, we simulate several counterfactual scenarios for the model under perfect competition. We have calibrated the model choosing values for F and α to obtain certificate prices equivalent to the tariffs and premiums, and renewable shares that replicate the market for every year of the whole period.

Policy makers set the level of these tariffs and premiums with the long-term perspective of achieving a 40% of gross inland electricity consumption from RES in 2020 (IDAE, 2012). These tariffs, however, induced an overinvestment in RES that caused higher shares of RES-E than expected from 2010 onwards (above 50%) at a disproportionate cost for consumers, but regulators were held captive by their own incentive system and any attempt to address the situation could not solve the problem (see Section 3.4.1).

We argue that a TGC system could authomatically adapt to any change in the electricity market conditions, avoiding some of the negative consequences of the FIT scheme. Since the actual regulator's preferences are not likely to change from year to year, we construct counterfactual scenarios based on a fixed RES target for the whole period 2008-2013 and we analyze how the TGC market evolves over time. Specifically, we take the target that replicates the share of Renewable Energy of 2009 ($\alpha = 0.44671$) and we assume it to be the value that represents the actual regulator's preferences for RES in Spain. Additionally, that share of RES-E produced on the spot market in 2009 is very close to the 40% of RES-E that was set as the target for 2020.[33]

In Table 3.3 (column in bold) we have chosen a particular combination of F and α from among the feasible values reported in Table 3.2 for the year 2009. If there had been a market for green certificates in 2009, they would have provided the same incentives as the FIT that were actually in place. Now we hold these values ($F = 7 \cdot 10^{-6}$ and $\alpha = 0.44671$) constant for the whole period 2008-2013 and derive the counterfactual market outcomes.

Figure 3.9 show time series for electricity prices, certificate prices and green quantities in equilibrium for the model keeping the regulatory parameters F and α constant for the whole period. Similarly, Table 3.5 presents more detailed figures, comparing actual electricity quantities (Q, Q_g), shares of RES-E (Q (%), Q_g (%)) and prices (p_e, p_{FIT}) to the counterfactuals ($\hat{Q}$, $\hat{Q}_g$, $\hat{Q}$ (%), $\hat{Q}_g$ (%), $\hat{p_e}$, $\hat{p_c}$). This is useful to see the effect of the quota of green electricity set by the regulator. Imposing the RES-E quota of 2009 onwards all the years, we observe the expected market replication for 2009. But what happens in the rest of the years? During 2008, simulated electricity prices are lower than actual prices, due to the fact that the share of RES-E is higher

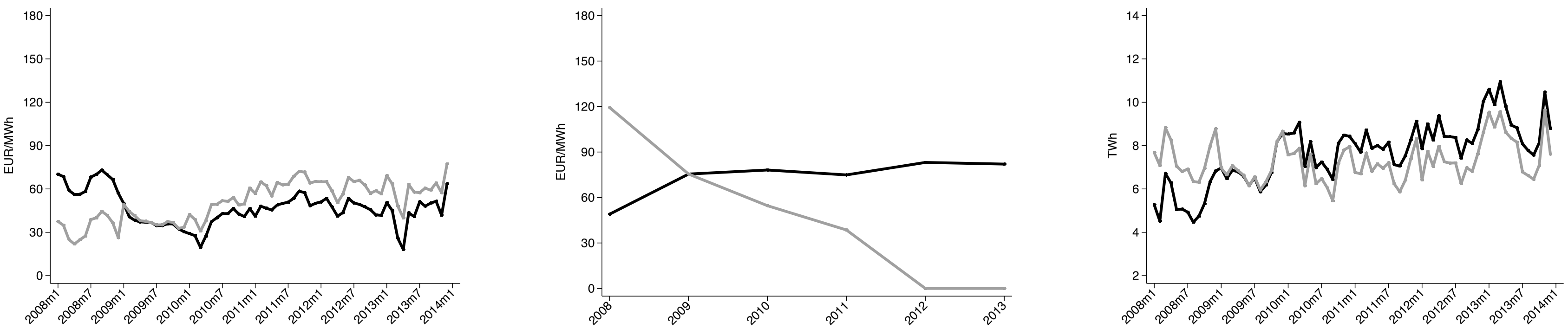
[33] As mentioned before, the savings from the market price reduction derived from the participation of renewable sources from 2010 onwards could not offset the increase in the regulatory costs of the incentive system (Ciarreta et al., 2014a). Therefore, we take the year 2009 as the benchmark: (i) before the breaking point took place and the regulatory system based on FIT was still efficient, and (ii) ensuring that the 2020 target for RES-E is achieved.

than actual data. At the same time, the certificate price for this year is higher than the price of the FIT. This means that if regulators set an ambitious target when renewable installed capacity is low, the price for certificates will be high (more support is needed). Concerning the period 2010-2013, simulated electricity prices are higher than actual prices, since actual renewable production is higher than the policy objective. Finally, in 2012 and 2013 the target for RES-E is fully met and because of that the price for certificates drops to zero.

Appendix C presents the results changing the benchmark year, which shows that the model is robust. It is also observed that if we use the target of 2008 (which is low) for the whole period, given the large RES-E available, we get zero prices for certificates from 2010 onwards (the target is fully met). On the other hand, if we use higher targets (2012-2013), certificate prices increase substantially for all the years in order for green shares to be higher than 45%.

FIGURE 3.9: Market data (black) vs. Model results (gray) with period parameters from 2009.

(A) Electricity Price (B) Certificate Price (C) Green Electricity



Source: Own elaboration based on data from OMIE (2015b) (electricity market data) and CNMC (2014a) (incentives).

TABLE 3.5: Model results with calibration for 2009.

year	α	Q_g %	$\hat{Q}_g$ %	Q_g TWh	$\hat{Q}_g$ TWh	Q TWh	$\hat{Q}$ TWh	p_e EUR/MWh	$\hat{p}_e$ EUR/MWh	p_{FIT} EUR/MWh	$\hat{p}_c$ EUR/MWh
2008	0.44671	28.3	36.0	65.52	83.61	231.48	232.46	64.43	46.61	49.01	141.66
2009	0.44671	39.7	39.5	81.92	82.34	206.42	208.38	36.96	38.16	75.46	75.46
2010	0.44671	47.9	42.4	94.01	82.61	196.35	194.8	37.01	45.56	78.13	38.98
2011	0.44671	51.6	44.1	95.48	80.39	185.10	182.09	49.93	63.40	74.89	7.29
2012	0.44671	55.1	45.9	102.28	81.84	185.77	178.37	47.23	62.11	83.12	0
2013	0.44671	58.9	49.0	109.82	89.2	186.59	181.86	44.26	64.63	82.04	0

Source: Own elaboration based on data from OMIE (2015b) (electricity market data) and CNMC (2014a) (incentives).

3.6 Policy implications

In the previous sections, we observed that when the Renewable Energy promotion is based on a TGC market, if Renewable Energy target is lower than actual production, certificate prices drop to zero. On the contrary, if the Renewable Energy target is higher than actual production, certificate prices will be positive. This argument has interesting policy implications in terms of the consumer burden of the regulatory policy. We now identify the system (FIT vs. TGC) that implements the desired amount of RES-E with the lowest cost, given the regulatory preferences defined by the tariffs (in the case of a FIT system) and α (in the case of TGC). In order to do it, we first compute the savings derived from RES-E participation through the merit order effect[34] (Table 3.7), we then obtain the costs driven by each incentive scheme (Table 3.8), and finally we substract them (Table 3.9).

In Section, 3.5 we defined a TGC market with the regulatory preferences for RES-E that achieve a renewable share of 40%, which replicates actual RES-E production in the Spanish pool in 2009. This section goes a step further and we work with different scenarios for the RES-E target, in order to compare the effect of regulatory decisions on the cost of the incentive scheme.

Table 3.6 presents the different scenarios, named after the target that was pursued in each of them, and the share of RES-E achieved with each of them. For instance, the 2009 target replicates the share of RES-E in 2009, which was 39.7% (in bold), and obtains different values for the rest of the years. Values in bold represent the year in which the TGC market was designed to replicate the share of RES-E that was actually produced in the Spanish pool under the FIT system, which indicates that figures in bold in Columns (3)-(8) and the value of the FIT scenario in Column (2) are comparable for each row. This also applies to Tables 3.7, 3.8 and 3.9.

Table 3.6: Share of Renewable Energy of certificates vs. tariffs [%].

year	FIT (Actual)	TGC (Model)					
		target 2008	target 2009	target 2010	target 2011	target 2012	target 2013
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
2008	28.3	**28.3**	38.0	42.8	45.2	46.6	47.0
2009	39.7	28.8	**39.7**	45.1	47.8	49.4	49.9
2010	47.9	34.0	43.0	**47.6**	50.0	51.3	51.7
2011	51.6	37.7	45.6	49.5	**51.5**	52.6	53.0
2012	55.1	41.0	48.3	51.9	53.8	**54.9**	55.3
2013	58.9	46.5	52.8	56.0	57.7	58.6	**58.9**

Source: Own elaboration based on data from OMIE (2015b) (electricity market data) and CNMC (2014a) (incentives).

[34]The merit order effect is the effect on spot prices of adding RES into the electricity market. This effect generally results in a price decrease. See Ciarreta et al. (2014a) for a detailed analysis on the merit order effect of Renewable Energy in Spain.

Starting with the cost calculation, Table 3.7 represents for each year in Column (1) actual market savings of RES-E[35] in Column (2) and market savings derived from the model in different scenarios in Columns (3)-(8). As stated before, each scenario is computed using a different target for RES, lower for the 2008 target (28.3%) and higher for the 2013 target (58.9%). Values in bold represent the year where the target of the TGC market replicates actual production under the FIT scheme, so those values are closer to actual merit order effects from Column (2). Similarly, Table 3.8 represents for each year the costs of the two incentive schemes: FIT in Column (2) and TGC in Columns (3)-(8). We again observe that the costs of the TGC system highlighted in bold approach the costs of the actual FIT scheme. All the figures in bold represent a TGC system equivalent to a FIT scheme and the other values are counterfactual results.

Table 3.7: Savings of RES-E: TGC vs. FIT [million EUR].

year	Merit order effect	Merit order effect (Model)					
	(Actual)	target 2008	target 2009	target 2010	target 2011	target 2012	target 2013
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
2008	7,397	**6,978**	5,374	4,294	3,775	3,186	2,761
2009	8,419	11,439	**8,775**	7,064	6,246	5,315	4,638
2010	6,962	10,695	8,503	**7,062**	6,430	5,719	5,205
2011	3,957	5,772	4,943	4,368	**4,085**	3,760	3,519
2012	5,237	7,648	6,613	5,888	5,530	**5,117**	4,820
2013	6,094	9,976	8,673	7,778	7,339	6,830	**6,459**

Source: Own elaboration based on data from OMIE (2015b) (electricity market data) and Ciarreta et al. (2014a) (actual merit order effect).

Table 3.8: Costs of RES-E: TGC vs. FIT [million EUR].

year	FIT (Actual)	TGC (Model)					
		target 2008	target 2009	target 2010	target 2011	target 2012	target 2013
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
2008	3,204	**3,183**	11,844	19,406	23,546	28,663	32,674
2009	6,169	1,227	**6,213**	10,712	13,197	16,284	18,711
2010	7,352	0	3,220	**7,281**	9,545	12362	14,583
2011	7,184	0	586	4,799	**7,161**	10125	12,480
2012	8,539	0	0	3,188	5,517	**8,458**	10,810
2013	9,061	0	0	1,172	3,572	6,542	**8,882**

Source: Own elaboration based on data from OMIE (2015b) (electricity market data) and CNMC (2014a) (incentives).

If we subtract the costs (Table 3.8) from the savings (Table 3.7) and compare the results under FIT and under TGC, we obtain the results set out in Table 3.9, which represents the effect of each regulatory policy on consumers. When the merit order effect savings are higher than the costs of the policy (positive values), the selected incentive scheme results in savings from the

[35] These values come from Ciarreta et al. (2014a).

consumer perspective. On the contrary, when the merit order effect savings are lower than the costs of the policy, the regulatory program results in costs from the consumer perspective.

Table 3.9: Savings (positive) or costs (negative) of certificates vs. tariffs [million EUR].

year	FIT (Actual)	TGC (Model)					
		target 2008	target 2009	target 2010	target 2011	target 2012	target 2013
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
2008	4,193	**3,795**	-6,470	-15,112	-19,771	-25,478	-29,913
2009	2,250	10,212	**2,562**	-3,647	-6,951	-10,969	-14,073
2010	-390	10,695	5,282	**-219**	-3,115	-6,643	-9,377
2011	-3,227	5,772	4,357	-431	**-3,076**	-6,365	-8,961
2012	-3,302	7,648	6,613	2,700	14	**-3,340**	-5,990
2013	-2,967	9,976	8,673	6,606	3,767	288	**-2,424**

Source: Own elaboration based on data from OMIE (2015b) (electricity market data), CNMC (2014a) (incentives) and Ciarreta et al. (2014a) (costs/savings with actual FIT).

We observe that the FIT system increased the consumer burden in Spain from 2010 onwards.[36] On the contrary, we conclude that a TGC with a low quota (target for 2008 and 2009) could have produced savings during practically the whole period. As we raise the quota, we detect higher costs for the TGC system. The highest cost values correspond to the 2013 target (58.9% of RES-E), but they still are lower than the costs of the FIT system for 2013. We highlight in gray the values for which the TGC system has lower costs than the FIT scheme.

When the target is lower, the TGC market results in cost-savings compared to the FIT system. However, this does not necessarily mean that our model replicates the levels of RES-E that were achieved under the FIT system every year, since that only happens for the benchmark year (data in bold in Tables 3.6, 3.7, 3.8 and 3.9) and not for the rest of the period. In fact, the share of green electricity in our model is always lower than the actual value when the cost-saving system is TGC, whereas the simulated share is higher than reality when the cost-saving system is FIT. This could be explained by the fact that the TGC market adjusts the level of green production according to the target of RES-E. If the target is too ambitious for the feasible levels of renewable output at the moment, the TGC system results in higher costs than the FIT scheme. On the other hand, if the target is set too low, the TGC system produces savings compared to FIT, but not enough renewable production, which is the case when we take the target from 2008. Anyway, considering that the target for 2009 was already enough to ensure the 2020 requirement for RES-E, we observe that a TGC system would have been more sustainable in terms of costs than a FIT scheme from 2010 onwards. Moreover, if we focus on the period 2011-2013, even if we had requested higher targets (targets from 2011 to 2013), the TGC system would have resulted in lower costs than FIT in all the scenarios, which proves that actual tariffs in 2012 and 2013 reached extremely high levels.

[36] Result from Ciarreta et al. (2014a).

Therefore, these results highlight the relevance of fixing the right quota, otherwise the TGC system could be too costly or induce too little RES production. In this sense, setting the level of the obligation in a system of certificates could be comparable to fixing the price of the tariffs and premiums in a FIT scheme, since in both cases a regulatory decision determines the level of subsidy given to RES-E. The difference lays in the fact that FIT are set for a longer time frame (10-20 years), whereas in a TGC model obligations could be defined for a shorter period (annually in our case, three years in the case of California's Renewable Portfolio Standard program, etc.).

Finally, our analysis assumes that agents are price takers and behave competitively; in particular, the supply of certificates must be competitive. The proposal of a TGC market would not be appropriate if the number of producers of a given technology is not large enough. Thus, a FIT system has proven to be more adequate for the initial stages of RES-E, but technologies are now mature enough to perform properly under a TGC scheme. Furthermore, in order for a TGC market to work properly, it is known that a minimum demand for certificates is also required. And this is precisely where the role of our quadratic penalty function lies. Thanks to the way we have designed the penalty function, the market is able to achieve a decreasing certificate demand enough to ensure the system functions properly.

3.7 Conclusions

On the verge of RES-E competitiveness, this chapter is based on the fact that most renewable technologies are currently still not ready to compete on the market without incentives, but at the same time they do not need anymore the high levels of support received in the past. After developing and implementing a theoretical model we show that if a TGC system had been implemented in Spain after 2009, the cost of the incentive scheme could have been lower than with the FIT scheme, and similar levels of renewable participation could have been achieved.

In this context, we analyze the interaction between the TGC market and the electricity market when both markets work under perfect competition. The highlight of our theoretical model is the design of the penalty function. We support the need for a quadratic penalty function based on the fact that the TGC market would not work if there was not a minimum demand for certificates. Our penalty function is thus seen as the device used to map retailers choices regarding green certificates into monetary losses. By means of a second-order penalty function, we model a decreasing demand for TGC, where higher deviations from the target are more heavily penalized than the smaller ones. The role of policy makers is crucial when setting the value for the scale parameter of the penalty function and the quota for green participation on the market.

The main point of the chapter is that a regulatory system based on TGC reacts to market changes while a FIT incentive scheme does not. To see how it reacts and how important this advantage of TGC is, we compare the actual evolution of an electricity market under FIT to a counterfactual under TGC. To build the counterfactual we first calibrate the model to obtain cost and demand parameters. We then set the incentives under TGC equal to those that were in place for a given year under FIT and derive the relevant regulatory parameters.

Our model shows that there is a transmission of market signals which makes the TGC market more efficient when compared to the FIT system. However, the role of regulators in TGC markets is still important, since setting the right target for RES-E affects the cost burden of the system considerably. If targets are set too low, little RES-E would be produced; but if targets are too ambitious, certificate prices would increase and TGC would be less efficient than a FIT system. Moreover, according to the results presented in this chapter, even with relatively high costs for green sources, the TGC model proves to be more sustainable than the Spanish FIT system for all the scenarios in 2013. Furthermore, if we consider the minimum requirement for RES-E for 2020 (40% of RES-E) in order to set the target, the TGC system results in lower costs than the FIT from 2010 onwards.

The numerical application of the model with actual data supports its feasibility in the Spanish electricity system, where renewable installed capacity is significant. But our model could be calibrated with data from any country. Furthermore, some of the assumptions could be relaxed in future versions, e.g. allowing certificates to have a longer lifetime, including different multipliers for some technologies or modeling uncertainty. This model is therefore a good initial approach for further research. In future research, we also propose to complete our model by including a multi-country market, due to the fact that a country with "cheap" RES-E, as would be the case of Spain, could then sell certificates to another country with more expensive Renewable Energy.

Finally, emission trading systems are another very interesting research line we should not overlook. Despite the fact that TGC and FIT are designed to support RES-E production rather than to reduce emissions, both goals are closely related. In fact, an increase in Renewable Energy may reduce emissions when there is a substitution effect of black energy with green energy. We should therefore analyze both markets individually (we only focused on TGC markets so far) but also the interactions between them.

Chapter 4

Evolve or die: Has Renewable Energy induced more competitive behavior on the electricity market?

4.1 Introduction

The entry of Renewable Energy Sources (RES, hereafter) on electricity markets has attracted a great deal of attention in recent years. Many empirical studies conclude that there has been a reduction of electricity prices, due to the merit order effect[37] (Sáenz de Miera et al. (2008), Sensfuss et al. (2008), Jónsson et al. (2010), Gelabert et al. (2011), Ciarreta et al. (2014a), among others). However, there has so far been little empirical research into the reaction of conventional producers to the introduction of green capacity resulting in a more competitive environment. This chapter addresses this issue. Did non-renewable generators change their bidding strategies as a result of the increasing renewable participation on the electricity market? Depending on the answer, the findings of previous merit order effect analysis could be reevaluated. On the one hand, price reductions entailed by RES could have been underestimated in previous research, if traditional sources should now bid at lower prices in order to avoid being displaced from the market by renewable units. From a theoretical perspective, this would be the expected result when a market becomes more competitive. On the contrary, the effect of RES could have been overestimated, if conventional sources had been bidding currently at higher prices or imposing more restrictions in order to limit the energy matched on the spot market. This would be the case if they could not afford to sell their energy, as market prices in the pool were below their

[37]The merit order effect is defined as the impact of Renewable Energy on the electricity price in the power market. Since RES usually bid at lower prices (even zero), their participation results in a reduction of wholesale spot prices.

unit production costs. In this case, they could refuse to participate on the spot market and transfer their production to adjustment markets[38] at higher prices.

This chapter analyzes behavioral changes after the entry of renewable generators on the Spanish electricity market. Our first result is that the effect on behavior was only noticeable for Combined Cycle bidding. While there was little change in other technologies, we do observe that Combined Cycle bidding strategies have evolved to adapt to the introduction of RES. Furthermore, with an increasing intermittent generation in the electricity system, the role of Combined Cycle units is crucial in order to ensure the security of supply.

After the massive entry of RES on the electricity market, Combined Cycle was the technology that suffered the most drastic reduction, both in production and in operating hours. According to data provided by the Spanish system operator (Red Eléctrica de España, REE hereafter), the utilization ratio[39] of Combined Cycle plants dropped from its maximum value of 52% in 2008 to its minimum value, 12%, in 2013 (REE, 2008, 2013). Moreover, Combined Cycle plants experienced a shift in their operating hours, from 5,119 production hours in 2005 (Navarro, 2011), to 1,000 in 2013, most of them assigned to comply with technical restrictions (CNMC, 2014c).

To detect any behavioral changes in producers' bidding, we combine the idea behind the Synthetic Control Approach by Abadie and Gardeazabal (2003) with the methodology to construct synthetic supply curves in Ciarreta and Espinosa (2010a,b) and the procedure to solve the electricity market equilibrium in Ciarreta et al. (2014a) (Chapter 2). We compute the counterfactual electricity spot market outcomes under different scenarios in order to detect whether Combined Cycle producers changed their bidding behavior after the massive entry of renewable production on the Spanish spot market. Ciarreta and Espinosa (2010a) used a synthetic approach to detect market power of large generators in the Spanish pool during the period 2001-2003, based on the different behavior of strategic and competitive generators. While Ciarreta and Espinosa (2010a) explored the effect of the size of the firms on market power, we here test whether there has been a behavioral change for the same technology in two different time intervals.

We select one year before RES took part actively on the market (*reference year*) to construct the synthetic supply curves and we consider different counterfactual scenarios for years with different shares of electricity from RES (*target years*). We choose 2008 as the reference year because RES production was beginning its ascent, but its level was still 59% of that reached in 2013, and at the same time most of the Combined Cycle capacity was already installed. Additionally, new regulation enacted in mid 2007[40] set a new framework for the RES incentive

[38]Adjustment markets include the resolution of technical restrictions, the allocation of ancillary services and the management of deviations.

[39]The utilization ratio is the ratio between actual and maximum available production or production that the power plant could reach operating at nominal capacity during the hours in which the plant is available.

[40]Royal Decree 661/2007 (BOE, 2007a).

regime in Spain and induced the actual boosting of RES on the electricity market.[41] The target years include an *ex-ante period* from 2002 to 2006, when renewable participation was moderate (in 2002, 31% of the level reached in 2013 and 42% in 2006); and an *ex-post period* from 2009 to 2013, when renewable production reached its maximum in Spain. The year 2007 is regarded as a transition period and therefore is not included.[42]

We consider actual values for electricity prices and two different synthetic scenarios for every target year.[43] In the first synthetic scenario, we take actual bids of Combined Cycle generators of the reference year to replace the bids of the year of analysis (e.g. we substitute the 2012 bids with the 2008 bids). In the second synthetic scenario, we take actual bids of Combined Cycle generators of the target years to replace the bids of the reference year (e.g. we substitute the 2008 bids with the 2012 bids). We do not change the demand in any scenario and we consider the change in behavior only for the Combined Cycle generating units present in both the reference and the target years, leaving the other units unchanged. Finally, we build synthetic bids with and without considering the change in gas prices, which provides us with a lower and upper boundary for the price change.

The chapter is structured as follows. First, Section 4.2 presents a descriptive analysis of the interaction between RES and conventional producers that suggests that Combined Cycle plants could have reacted to the presence of RES, whereas other technologies remained almost unaffected. Afterwards, Section 4.3 provides the details of the procedure to build the synthetic supply curves. We present and discuss the results of our simulations under the different scenarios in Section 4.4 . Finally, concluding remarks follow in Section 4.5.

4.2 The interaction between Renewable Energy and conventional producers

The participation of RES on the Spanish electricity market has been increasing in the last decade. According to data published by the Spanish market operator (Operador del Mercado Ibérico de Electricidad, OMIE hereafter), only 11% of total production on the spot market came from RES in 2005. By 2008 this share had reached 33% and it was already over 60% by 2013 (OMIE, 2015a). As a result of the merit order effect induced by the massive introduction of RES, annual average electricity prices dropped significantly, i.e. from 64 EUR/MWh in 2008 to 44 EUR/MWh in 2013 (see Ciarreta et al. (2014a), Chapter 2). Thus, conventional producers[44],

[41] For a detailed analysis on the effect of Royal Decree 661/2007 (BOE, 2007a) on renewable production see Ciarreta and Pizarro-Irizar (2014).

[42] For a detailed analysis on the evolution of RES participation on the Spanish electricity market see Ciarreta et al. (2014a) (Chapter 2).

[43] Note that all the synthetic scenarios reflect counterfactual situations.

[44] We include Nuclear, Hydropower, Coal and Combined Cycle plants as conventional producers.

which are the marginal units on the spot market, could have reacted to this price decrease in several ways.[45] In terms of prices, they could be currently bidding lower than in the ex-ante period, to avoid being withdrawn from the market. On the contrary, if they try to exert a certain degree of market power and hold prices high to maximize their profits, their price bids could have been higher. In terms of quantities, they could be restricting the energy sold on the spot market at low prices in the ex-post period, in order to participate in adjustment markets[46], where prices are generally higher.

This section analyzes the evolution of several variables that could affect the interaction between renewable energy and conventional producers. In particular, the installed capacity, production shares and utilization ratio of all technologies taking part in the Spanish electricity mix: Nuclear, Hydropower, Coal, Combined Cycle and Special Regime.[47] In principle, any of the conventional producers could be experiencing a behavioral change after the development of RES. However, we find empirical evidence suggesting that Combined Cycle plants are the most likely candidate for changes in bidding strategies.

First of all, comparing the evolution of the installed capacity by technology during the period 2002-2013, we observe in Figure 4.1 that both Special Regime and Combined Cycle plants were the technologies receiving the highest investments. While the installed capacity of Nuclear (Figure 4.1a), Hydropower (Figure 4.1b) and Coal plants (Figure 4.1c) remain almost constant during the analyzed decade (1%, 7% and -4%, respectively), there were important capacity increases for Combined Cycle units (719%, Figure 4.1d) and Special Regime technologies (225%, Figure 4.1e) from 2002 until 2013. Furthermore, Special Regime and Combined Cycle can be considered as substitutes in terms of investments. That is, the sharpest rise in installed capacity for gas plants took place right before 2007, which is precisely the moment when RES were boosted in Spain, and afterwards investments were transferred from Combined Cycle technologies to green energy. This breakdown could be consequence of Royal Decree 661/2007 (BOE, 2007a), which was passed in May 2007 and established a new framework for the RES incentive regime in Spain.

We now examine the supply curves for the Spanish spot market. Figure 4.2 shows annual aggregate supply curves and individual supply curves by technology. As mentioned before, taking Royal Decree 661/2007 (BOE, 2007a) as the element inducing a hypothetical strategic change, we plot aggregate supply curves for the ex-ante period from 2002 to 2006 (solid black line) and the ex-post period for 2009-2013 (dashed black line) and we exclude 2007 and 2008

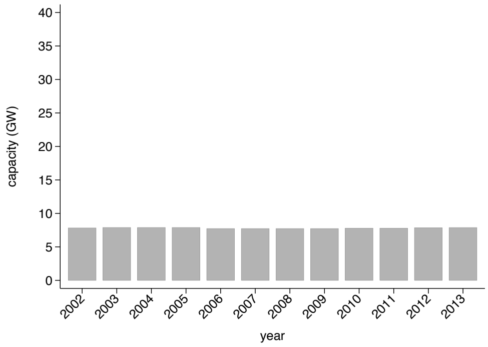
[45] Wolak and Patrick (1996) claim that there are two strategic weapons available for electricity generators: first, the maximum amount of capacity made available at the pool and, second, the price bids.

[46] According to the rules of the Spanish electricity market (OMIE, 2007), producers must offer all their capacity on the spot market in order to be allowed to participate in adjustment markets. However, they could bid most of their capacity at high prices to make sure that it is not matched in the pool and sell it more profitably on the subsequent adjustment markets. We will explore this issue in the following sections.

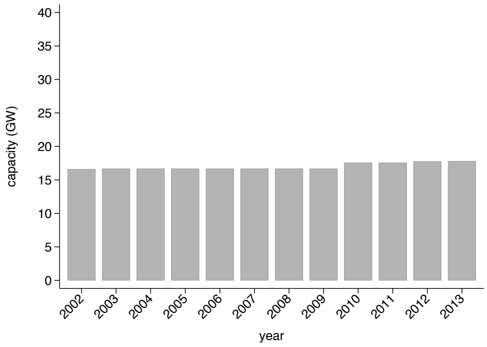
[47] Special Regime includes RES (Wind, Solar Photovoltaic, Solar Thermal, Small Hydro power and Biomass/Wastes) and Cogeneration. The Special Regime was cancelled in 2014.

FIGURE 4.1: Evolution of the installed capacity by technology [GW]. Period 2002-2013.

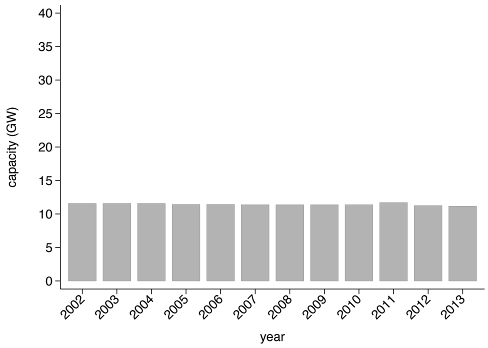
(A) Nuclear



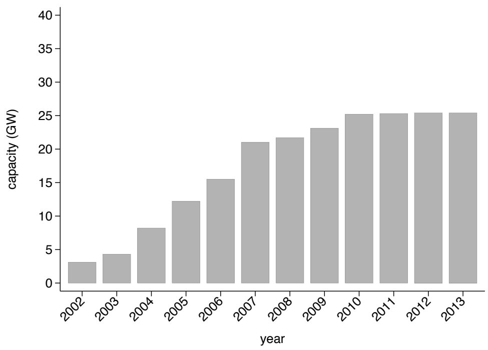
(B) Hydropower



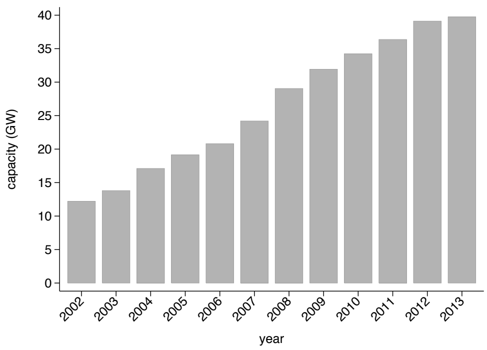
(C) Coal



(D) Combined Cycle



(E) Special Regime



Source: Own elaboration, data from REE (2002) - REE (2013).

as the transition years. We observe that the slope of the aggregate supply curves (Figure 4.2a) after 2008 is lower than in the previous period (27% lower in a linear fit). This effect could be due to the increment in RES capacity occurring in recent years, but it could also indicate a change in the bidding strategy of some agents. In fact, if we represent the aggregate supply without RES (Figure 4.2b), we observe that both curves are much closer. However, we still detect a change between both curves, since the dashed line is flatter.

In order to identify possible behavioral changes, we isolate the supply curves for each of the participant technologies and we analyze them individually. We focus in all cases on the segment at minimum and maximum prices and on the slope of the supply curves. Figure 4.2a suggests that there could have been a flattening effect on the aggregate supply curves after the introduction of Renewable Energy, and this pattern holds even when we remove renewable sources from the supply curve (Figure 4.2b), which suggests changes in the bidding strategies of other actors.

We also observe that, as expected, changes in the slope of Nuclear (Figure 4.2c) supply curves are negligible[48], since it is a baseload technology. Even Hydropower (Figure 4.2d), does not exhibit a clear variation in the ex-ante and ex-post curves. Their pattern seems to respond mainly to the rainfall of each period[49] rather than to renewable participation.

However, there are higher changes for Coal producers (Figure 4.2e). Coal plants have been influenced by several facts during the ex-post period: coal prices, emission prices and regulation. First of all, according to the McCloskey index[50], international coal prices started to increase significantly from 2003 on. Additionally, the Emission Trading System in Spain was regulated in 2005[51] and Coal producers have internalized carbon emission prices in their bids from then on (Chen et al., 2008; Fabra and Reguant, 2014), resulting in higher prices from 2005 onwards. This is consistent with what is observed in Figure 4.2e, where the energy offered at lower prices, with almost the same capacity in both ex-ante and ex-post periods, is higher before 2006. Finally, domestic coal industry benefited from a special regulation from 2010 on (we will discuss it in greater detail later on), which could also have affected their bidding strategies in the pool.

Finally, we detect that the greatest flattening pattern is due to Combined Cycle generators (Figure 4.2f). The slope of the aggregate supply curve (linear fit) is 69% lower during the ex-post period and the amount of energy offered at maximum prices (180.3 EUR/MWh) is also the highest. It is true that there has been an important capacity increase (Figure 4.1) for this technology, which could have affected the position of the supply curves, but the slope difference

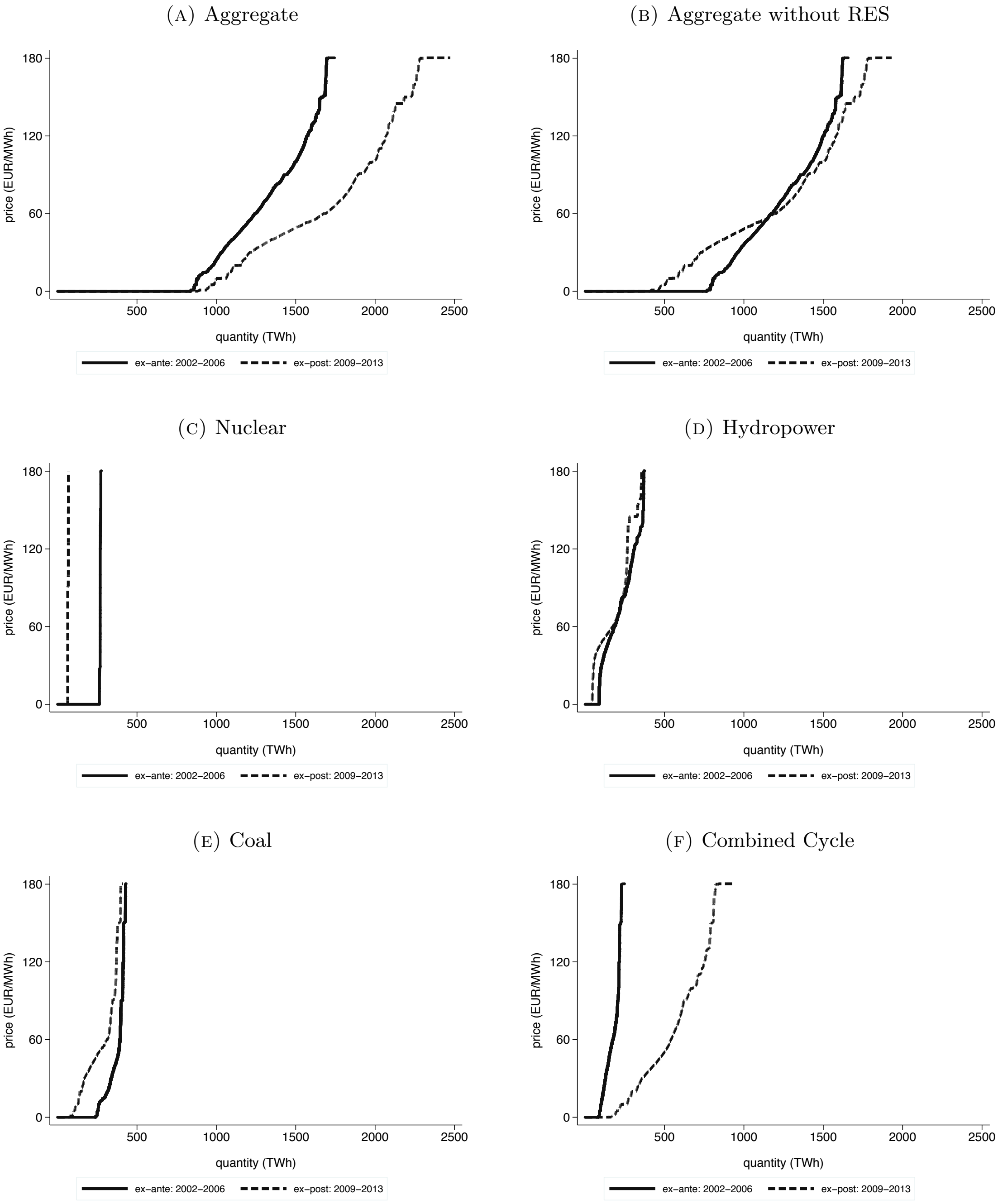
[48]We note a difference in the quantity offered at zero prices, which is lower during the ex-post period, but this effect is independent of Renewable Energy. It is due to the fact that nuclear plants after 2006 started to sell part of their electricity via bilateral contracts and not in the pool (Armstrong et al., 2014). Final production, however, did not change (REE (2002)-REE (2013)).

[49]The ex-ante period was overall dry, but there are fluctuations in the ex-post period, where the low rainfall of 2009, 2011 and 2012 contrasts with the high precipitations of 2010 and 2013, according to REE (2002)-REE (2013).

[50]Carbunion (2006)-Carbunion (2013)

[51]Law 1/2005 (BOE, 2005)

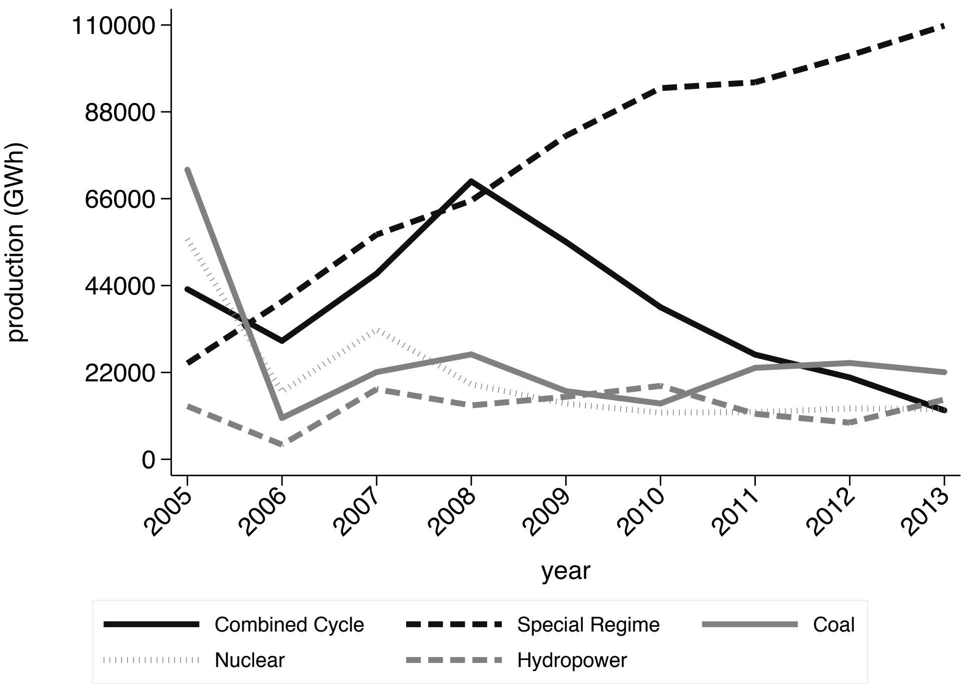
Figure 4.2: Aggregate Supply on the Spanish spot market in the ex-ante (2002-2006) and ex-post (2009-2013) period.



Source: Own elaboration, data from OMIE (2015b) (hourly bids) and REE (2002) - REE (2013) (technology identification).

seems to be rather high, so we continue exploring whether a direct relationship exists between RES and Combined Cycle bidding behavior.

FIGURE 4.3: Evolution of electricity production on the spot market by technology [GWh]. Period 2005-2013.



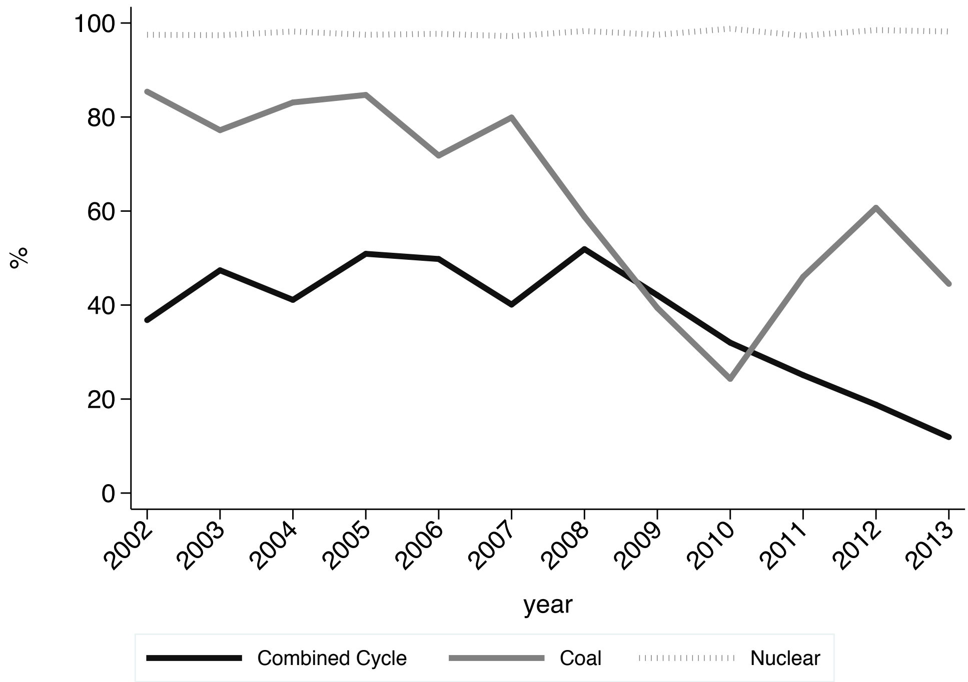
Source: Own elaboration, data from OMIE (2015a).

After examining the changes in installed capacity and the shape of the supply curves, we analyze the relationship between RES and Combined Cycle in terms of electricity production on the spot market. Figure 4.3 represents the evolution of electricity production in the pool by source from 2005[52] until 2013. We observe that RES (black dashed line) were the only technologies that show constant growth from the beginning of the period. For the rest of the sources in the Spanish electricity mix, Combined Cycle production (black solid line) experienced a significant decrease from 2008 on, while Nuclear (gray dashed line), Hydropower (gray dotted line) and Coal (gray solid line) remained relatively steady.

Finally, we analyze the capacity utilization ratio of the thermal technologies in Figure 4.4. Hydropower is not represented, since it depends on rainfall and annual reserves. Similarly, most of the production of RES comes from Solar and Wind, which also relay on the weather and therefore it is not considered for this ratio. We detect changes for Coal (gray line) and Combined Cycle (solid line) technologies, whereas Nuclear (dotted line) remains constant over time.

[52]Data for 2002-2004 are not available.

FIGURE 4.4: Evolution of the capacity utilization ratio for the thermal technologies [%]. Period 2002-2013.



Source: Own elaboration, data from REE (2002) - REE (2013).

Concerning Coal's capacity utilization ratio, we do not identify any specific pattern that could be related to RES production. There has been an important drop from 2007 (80%) to 2010 (24%), coinciding with higher prices for coal and the introduction of the Emission Trading System. This trend ended after regulation to drive consumption of domestic coal in February 2010.[53] As a result, there was a recovery in the capacity utilization ratio of this technology until 2012 (61%). However, both production and utilization ratio of Coal units dropped again in 2013 as a consequence of new regulations.[54]

In the case of Combined Cycle plants, we observe a clear decrease in the capacity utilization ratio after the boost of RES, from the maximum value of 52% in 2008 to the minimum of 12% in 2013. This trend is clearly present in Figures 4.3 and 4.4. All in all, this preliminary evidence points to a relationship between the increase of RES and the decline of Combined

[53]The passing of Royal Decree 134/2010 (BOE, 2010d), amended by Royal Decree 1221/2010 in October 2010 (BOE, 2010e). This decree established that, under certain circumstances, a certain amount of energy that had already been matched in the daily market could be removed and replaced by the production of other plants using domestic coal.

[54]Price and volume parameters associated to coal are defined annually by means of an official resolution by the Secretary of State for Energy. In 2013 (BOE, 2013c), coal prices in the corresponding resolution did not include the new taxes affecting the price of coal (BOE, 2012c) and therefore induced a new drop in the production of this technology.

Cycle production. We will try to establish in the following sections whether there has been a behavioral change in the bidding strategies of Combined Cycle.

4.3 Empirical strategy and data

We here justify the existence of strategic behavior on the Spanish electricity market and describe a procedure to identify bidding changes for Combined Cycle producers.

4.3.1 Strategic behavior on electricity markets

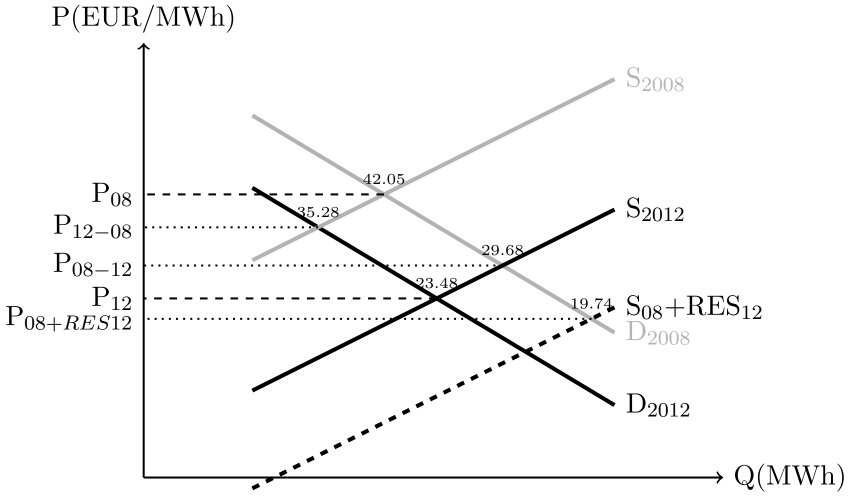
Strategic behavior on electricity markets has been widely analyzed in existing literature. Several papers provide evidence of strategic bidding on international electricity markets (Wolak (2000) for Australia, García-Díaz and Marin (2003) and Ciarreta and Espinosa (2012) for Spain, Crawford et al. (2007) for the British market, Hortacsu and Puller (2008) analyze the case of Texas and Bosco et al. (2012) focus on Italy). All these authors describe the optimal bidding behavior of electricity producers through the combination of actual data and theoretical models. They compare actual bidding behavior to theoretical benchmarks and, measuring the differences, they are able to identify strategic bidding. The main hypothesis behind this research line is the existence of bid markups, which reflect the difference between the cost of producing electricity and its selling price. There would be no markups in a perfectly competitive market, but there is scope for strategic behavior as long as their value differs from zero. The empirical literature widely supports the existence of strategic behavior on electricity markets (see also von der Fehr and Harbord (1993), Wolfram (1999) and Borenstein et al. (2000), among others).

We wish to detect in this chapter if there have been any strategy changes after the massive introduction of RES. In order to do this, we implement a new way of detecting changes in strategic behavior on electricity markets, based on the comparison between actual and synthetic bidding behavior of generation units. Since we have all the necessary information on the bids of all the agents in the Spanish pool (OMIE, 2015b), we are able to replicate the actual equilibrium situation and simulate counterfactual scenarios. The comparison of observed and simulated market outcomes allows us to identify possible changes in the bidding strategies of electricity producers; the key is to set the appropriate counterfactuals.

The question we pose is: Did electricity generators modify their strategic behavior in the Spanish pool after the entry of RES? One possibility is the comparison of the supply curves before and after the entry. In principle, we expect supply curves after RES to be closer to the marginal cost curves (more competitive). The drawback is that measuring the distance to the marginal cost function is not straightforward.

Behavior can be considered more competitive if, ceteris paribus, the resulting equilibrium price is lower. For instance, we take two years -2008 (moderate presence of RES) and 2012 (high presence of RES)- and we try to detect possible changes in strategic behavior. Figure 4.5 represents annual equilibrium prices for 2008 and 2012 as the intersection of demand and supply under different scenarios. All the prices have been calculated using the market algorithm developed in Ciarreta et al. (2014a) (Chapter 2), which computes the hourly equilibrium price and quantity based on the bids of all agents participating in the pool. Then, we calculate the annual weighted average for each scenario as $p = \frac{\sum_h^H p_h \cdot q_h}{\sum_h^H q_h}$, where p_h is the hourly electricity price, q_h is the hourly quantity traded and H is the total number of hours in the corresponding year.

FIGURE 4.5: Market equilibrium 2008 vs. 2012.



Source: Own elaboration, data from OMIE (2015b).

Actual equilibrium prices for 2008 and 2012 are 42.05 EUR/MWh and 23.48 EUR/MWh, respectively (see the intersection of gray and black lines, respectively). Comparing both prices, there is a reduction of 18.57 EUR/MWh. However, this price reduction cannot just be interpreted as a result of a more competitive behavior of producers, because there have also been changes in the demand between these two years. With the 2008 demand, as if it had been the demand of 2012, the price in 2012 would have been 29.68 EUR/MWh. The difference of 6.2 EUR/MWh between 29.68 EUR/MWh and 23.48 EUR/MWh is due to the drop in demand (due to the economic crisis) and not to the fact that the market was actually more competitive. But still, the decrease of 12.37 EUR/MWh from 42.05 EUR/MWh to 29.68 EUR/MWh is attributable to the supply rise from 2008 (S_{2008}) to 2012 (S_{2012}). Thus, we can decompose the total price change (42.05 EUR/MWh - 23.48 EUR/MWh = 18.57 EUR/MWh) into a demand-induced price change (29.68 EUR/MWh - 23.48 EUR/MWh = 6.2 EUR/MWh) and a supply-induced price change (42.05 EUR/MWh - 29.68 EUR/MWh = 12.37 EUR/MWh).

Similarly, considering again the demand and supply in 2008 as the reference point, and taking the supply of 2012 as if it had been the 2008 supply, we find a new counterfactual equilibrium situation. The total price change can be then decomposed in a demand-induced price change (42.05 EUR/MWh - 35.28 EUR/MWh = 6.77 EUR/MWh, where 35.28 EUR/MWh is the equilibrium price with the 2008 supply (S_{2008}) and the 2012 demand (D_{2012})); and a supply-induced price decrease (35.28 EUR/MWh - 23.48 EUR/MWh = 11.8 EUR/MWh). We can see with any of the two procedures that changes in the supply were responsible for approximately two thirds of the price change, while demand-induced changes account for one third of the price variation between 2008 and 2012.

The next step is to identify if the change in the supply curve from 2008 to 2012 is exclusively due to the renewable capacity increase, or if there has been a more competitive behavior affecting price formation. In order to isolate these two effects, we represent the supply curve $S_{08}+RES_{12}$ (dashed black line). This curve has been computed as the existing supply in 2008 plus the Renewable Energy added during the period 2008-2012.[55] We observe that the curve $S_{08}+RES_{12}$ is to the right of S_{2012}, which means that firms had a less competitive market behavior (in 2012 than in 2008), according to our previous definition.[56]

It is remarkable that generators' behavior was less competitive in 2012 than in 2008 (supply curve to the left) in a more competitive environment (a higher number of competitors and more capacity with low marginal cost). This apparent paradox will be dealt with in the following sections with our synthetic bidding simulations, where we will identify the changes in the strategic behavior of Combined Cycle producers.

4.3.2 Synthetic Bidding for Combined Cycle plants

In the previous sections, we presented evidence that the entry of RES in the Spanish pool affected the bidding of Combined Cycle plants and their behavior appeared to be less competitive in 2012, but more competitive if we look at the period 2009-2013 (see Figure 4.2f). Our goal is to identify these possible strategic changes for Combined Cycle producers. This section describes how we proceed to identify this non-competitive behavior.

The Spanish pool[57] works as a uniform price auction where both supply and demand side submit their bids. These bids, which are called Simple Bids, consist of a pair price (p) and quantity (q) and they can include between 1 and 25 energy blocks submitted at different prices in each hour: $b_h = \{(q_h, p_h)_i\}$ with $i = 1, 2, \ldots, 25$ and $h = 1, 2, \ldots, 24$. Prices range from 0 to 180.3

[55] Note that the capacity increase in the period 2008-2012 was for the most part renewable capacity (see Figure 4.1).

[56] Note also that the capacity of Nuclear and Hydropower where 2% and 7% lower, respectively, in 2008 than in 2012; and Coal capacity was 1% higher. Therefore, these technologies cannot account for the inward shift of supply, since with the exception of coal, capacity was slightly higher in 2012.

[57] See Ciarreta and Espinosa (2010b) for a detailed information on the Spanish pool.

EUR/MWh and the market clears every hour. Additionally, there are Complex Bids, which incorporate technical or economic conditions such as indivisibility, load gradient, minimum revenue or scheduled stop. These Complex Bids affect price formation because they retrieve energy from the matching process when certain conditions do not hold. Complex Bids may also contain a certain degree of strategic behavior (Reguant, 2014), but identifying non-competitive behavior using only Simple Bids is also a good indicator of strategic bidding.

We follow the idea behind the Synthetic Control Approach by Abadie and Gardeazabal (2003, 2008) in order to detect strategic changes due to RES.[58] To measure the economic impact of a certain event, they build a counterfactual situation eliminating the event subject to analyze and compare actual with counterfactual variables. If there has been a true effect after the event, while counterfactual results prior to it would not differ very much from observed values, results after the event would show deviations, proving that the event had an actual effect.

In our case, the event we want to analyze is the massive deployment of RES in the Spanish pool. We set a reference year where the participation of RES was still moderate (year 2008, with 65,575 GWh and 23% of total share) and we compare it to a period where there was little Renewable Energy on the market (the ex-ante period, from 2002 to 2006, with 33,682 GWh to 46,348 GWh and 15% to 20% of total share) and to a period of high penetration of RES (the ex-post period, from 2009 to 2013, with 82,065 GWh to 110,237 GWh and 31% to 44% of total share).[59]

In order to compute our counterfactual scenarios (synthetic scenarios), we use the hourly bids of the Spanish electricity market provided by OMIE (2015b) and data from the Spanish electricity system operator to identify the units corresponding to each technology (REE (2002)-REE (2013)). Actual bids (b_a^Y) for one representative hour of the year Y have the following form:

$$b_a^Y = \{(q,p)\}^Y = \{(q_{NU}, p_{NU})^Y, (q_{HY}, p_{HY})^Y, (q_{CT}, p_{CT})^Y, (q_{CC}, p_{CC})^Y, (q_{SR}, p_{SR})^Y\},$$

where NU stands for Nuclear, HY for Hydropower, CT for coal, CC for Combined Cycle and SR for Special Regime (RES and Cogeneration). The hourly supply curve for a given year, month, day and hour is computed in two steps: first, we sort prices from zero to the maximum price and, second, we sum up the quantities. Following the same approach, synthetic hourly bids (b_s^Y) are built from actual bids changing the price and quantity pair for Combined Cycle units to the actual values in a different year Y':

$$b_s^Y = \{(q,p)\}^Y = \{(q_{NU}, p_{NU})^Y, (q_{HY}, p_{HY})^Y, (q_{CT}, p_{CT})^Y, (q_{CC}, p_{CC})^{Y'}, (q_{SR}, p_{SR})^Y\},$$

where Y is the original year and $Y' \neq Y$ is the year we use to build the counterfactual.

[58] Another possible approach is structural change identification, based on time series analysis (Henry, 2000).

[59] As mentioned before, we consider that the starting point of actual renewable deployment was Royal Decree 661/2007 (BOE, 2007a), which was passed in 2007. Therefore, we do not consider 2007 in our analysis, since it is a transition year.

We design two different synthetic scenarios: the Dynamic Synthetic Scenario and the Static Synthetic Scenario. In the first one, the Dynamic Synthetic Scenario (dynamic because we observe the behavior for each year in a timeframe of ten years: five for the ex-ante period and five for the ex-post period), we take actual bids of Combined Cycle generators of the reference year ($Y' = 2008$) to replace the bids of the year of analysis ($Y = 2002-2006$ or $Y = 2009-2013$) without changing the bids of the other agents. Taking, for example, the year 2012 as the target year (Y) and the year 2008 as the reference year (Y'), the synthetic bid structure for 2012 is:

$$b_s^{2012} = \{(q_{NU}, p_{NU})^{2012}, (q_{HY}, p_{HY})^{2012}, (q_{CT}, p_{CT})^{2012}, (q_{CC}, p_{CC})^{2008}, (q_{SR}, p_{SR})^{2012}\}.$$

The Static Synthetic Scenario (static because we observe the behavior only for the year 2008) is exactly the opposite exercise. We take actual bids of Combined Cycle generators of the target years 2002-2006 and 2009-2013 to replace the bids of the reference year 2008. Taking again the year 2012 as the target year, the synthetic bid structure for 2008 is:

$$b_s^{2008} = \{(q_{NU}, p_{NU})^{2008}, (q_{HY}, p_{HY})^{2008}, (q_{CT}, p_{CT})^{2008}, (q_{CC}, p_{CC})^{2012}, (q_{SR}, p_{SR})^{2008}\}.$$

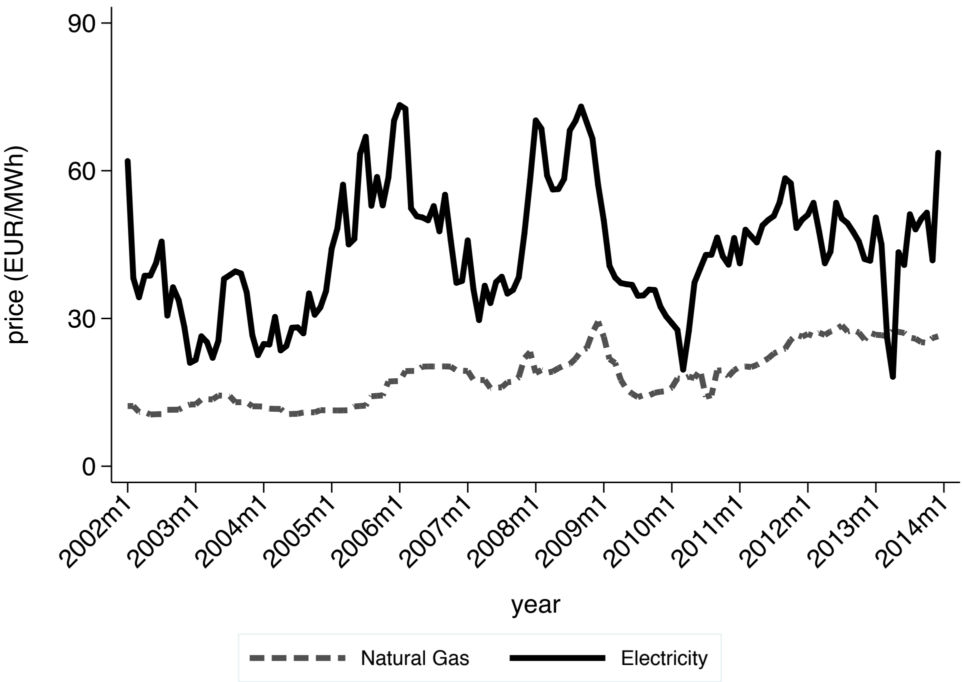
Additionally, for each scenario (dynamic and static) we build two different synthetic bids for Combined Cycle producers. In one case we import the bids of Combined Cycle units from the original year and we assume that there are no external factors affecting them (only strategic behavior). However, there is empirical evidence of the correlation between electricity and natural gas prices (Furió and Chuliá, 2012), as shown in Figure 4.6.[60]

Therefore, in our second subscenario we modify the price bids of Combined Cycle producers to incorporate the percentage change in gas prices. For instance, if gas prices in 2008 were lower than in 2012, synthetic bids for Combined Cycle in the Dynamic Synthetic Scenario for 2012 would be higher than actual bids of 2008. On the contrary, synthetic bids for Combined Cycle in the Static Synthetic Scenario for 2008 would be lower than actual bids of 2012. In order to update actual gas prices in our synthetic bids, we take natural gas prices for Spain from the National Energy Commission (CNMC, 2015b) and we change the bids with prices higher than 5 EUR/MWh. Observing carefully the bidding structure of Combined Cycle units we note that independently of gas prices, producers always offer a certain amount of energy at prices lower than 5 EUR/MWh, a consequence of their start-up costs rather than fuel prices, as they are interested in selling a positive amount at any price. Finally, it is worth mentioning that in both cases we take only the common generating units in both reference and target year (new unit behavior is kept unchanged) and we adapt the quantity bids to the actual capacity of Combined Cycle plants for the year to analyze.

Figure 4.7 represents the distribution of the energy bids of Combined Cycle units. The y-axis represents the share of energy (in %) offered at each price over the total energy offered by

[60]Electricity price spikes are correlated with local maxima of the curve on gas prices.

FIGURE 4.6: Evolution of Natural Gas and electricity prices [EUR/MWh]. Monthly basis. Period 2002-2013.



Source: Own elaboration, data from OMIE (2015c) (hourly electricity prices) and CNMC (2015b) (monthly gas prices).

Combined Cycle units, and the x-axis displays the range of possible prices (from zero to 180 EUR/MWh). As an example, we take one year from the ex-ante period (2004) and two years from the ex-post period, one at the beginning of the period (2010), which we call the early ex-post, that includes the years 2009 and 2010; and another at the end of the period (2012), what we call the late ex-post, that includes the period 2011-2013. The rest of the years of each period exhibit the same pattern as their corresponding representative year. We represent the distribution of actual bids (left), synthetic bids with original gas prices (middle) and synthetic bids considering the change in gas prices (right). Comparing actual prices, we observe a change in the bidding structure. During the ex-ante period, Combined Cycle producers offered most of their energy at zero price. On the contrary, during the ex-post period we observe few bids at zero price and a more widespread distribution of the bids. Finally, considering the maximum price, we detect that in the last years of the ex-post period, Combined Cycle bidders offer more energy at this price.

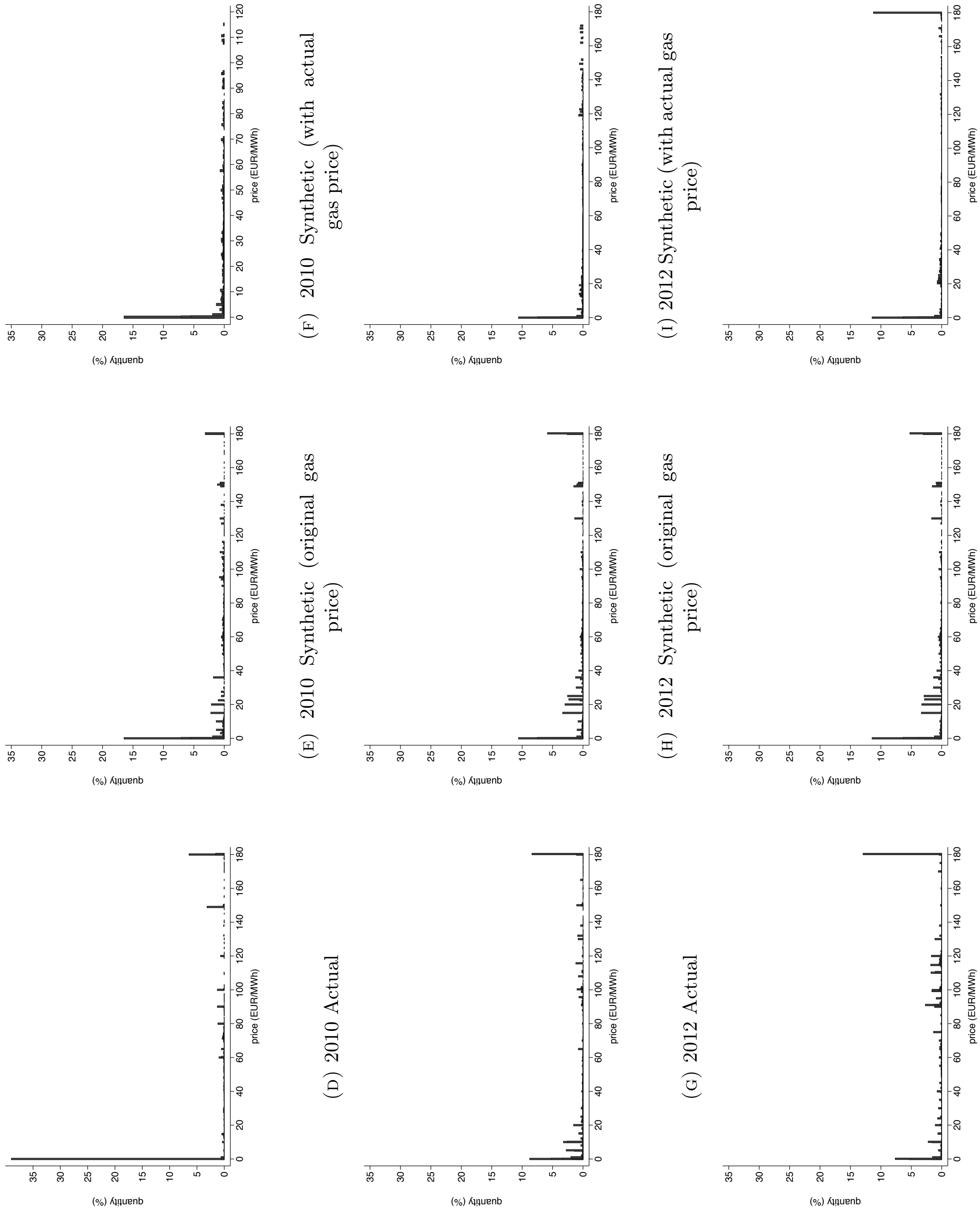
Concerning the synthetic bidding structures, they are quite similar for the three years (2004, 2010 and 2012). This is consistent with the fact that we have used the actual bids of the year 2008 for the whole period. Small changes are due to the fact that we changed only the common units (new units and closures have not been changed). Comparing actual and synthetic bids we detect that during the ex-ante period, the share of synthetic energy bids at zero price reduces considerably. However, during the ex-post period, synthetic bids at zero price seem to increase and synthetic bids at maximum price seem to reduce, suggesting that Combined Cycle producers could have been bidding differently after the entry of RES. Finally, note that synthetic bids with actual gas price are lower than synthetic original bids for 2004 and 2010 and higher for 2012. This is due to the fact that natural gas prices for Spain in 2008 where higher than in 2004 and 2010 and lower than in 2012.

Table 4.1 summarizes the synthetic scenarios and the procedures for the simulations.

Table 4.1: Methodology and synthetic scenario classification.

1. Actual Scenario (actual outcomes):
   - Take actual bids and run our market clearing algorithm from Ciarreta et al. (2014a) (Chapter 2) to get the actual equilibrium prices.
   - Compute it for the reference year and all the target years in the ex-ante (2002-2006) and ex-post (2009-2013) periods.
   - This is the benchmark for other scenarios.
2. Dynamic Synthetic Scenario:
   - Take actual bids of Combined Cycle generators of the reference year to replace the bids of the target year.
   - Run the market clearing algorithm.
   - No change in demand.
   - Replace only the bids of the common generating units.
3. Static Synthetic Scenario:
   - Take actual bids of Combined Cycle generators of the target years to replace the bids of the reference year.
   - Run the market clearing algorithm.
   - No change in demand.
   - Replace only the bids of the common generating units.

Figure 4.7: Distribution of Simple Energy Bids of Combined Cycle plants: Actual vs. Synthetic [%].



(A) 2004 Actual

(B) 2004 Synthetic (original gas price)

(C) 2004 Synthetic (with actual gas price)

(D) 2010 Actual

(E) 2010 Synthetic (original gas price)

(F) 2010 Synthetic (with actual gas price)

(G) 2012 Actual

(H) 2012 Synthetic (original gas price)

(I) 2012 Synthetic (with actual gas price)

4.4 Results and Discussion

4.4.1 Actual and synthetic electricity price series. Descriptive statistics

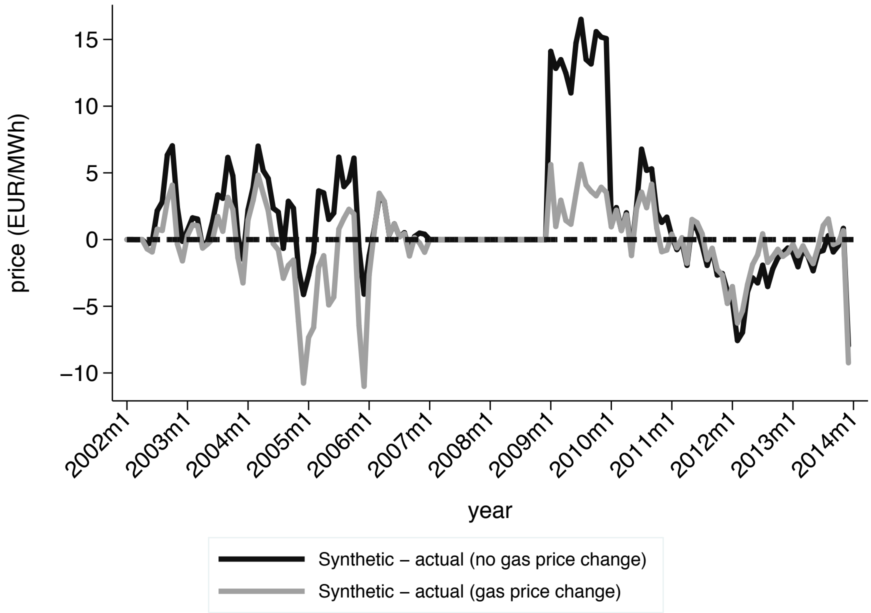
Figure 4.8 compares price differences ($p_{synthetic} - p_{actual}$) for the synthetic prices based on original bids of the reference year (solid black line) and the synthetic prices including the change in natural gas price (gray line). Monthly weighted average prices are computed as the weighted average of hourly electricity prices for one month: $\frac{\sum_h^H p_h \cdot q_h}{\sum_h^H q_h}$, where p_h is the hourly electricity price, q_h is the hourly quantity traded and H is the total number of hours in the corresponding month. In this case, synthetic supply curves where computed with the methodology for the Dynamic Synthetic Scenario (2008 is the reference year and 2002-2006 and 2009-2013 are the target years). Figure D.1 in Appendix D presents the price differences computed with the methodology for the Static Synthetic Scenario.

We observe that price difference between the synthetic series including the change in the gas price is generally lower (closer to the zero line) than the price difference of the synthetic series computed using original bids. This is due to the fact that gas prices in 2008 were higher than for any other year of the analyzed period (see Figure 4.6), which forces synthetic bids -and therefore electricity prices- to be lower in the scenario that considers the change in the gas price, since we have reduced actual bids of 2008 by the same percentage as gas prices lowered for every year. The fact that series including the change in gas prices are closer to observed prices than series computed with original bids suggests a pass-through of natural gas prices into the bids of Combined Cycle generators, in line with the findings by Furió and Chuliá (2012).

However, we found an exception during some months of the year 2005, where we obtain higher price deviations for the synthetic series with change in gas prices. This could be due to the fact that 2005 was an extremely dry year (REE, 2005), which makes prices fall more than usual when we generate synthetic bids including gas prices (note that Figure 4.6 showed that natural gas prices were higher in 2008 than in 2005, so synthetic bids for 2005 are lower than actual bids for 2008). We also detect abnormally high price deviations in 2009 for the series without change in gas price, which could be due to the fact that gas prices in 2009 were generally low and that could have affected the bids. We do not observe either of these effects in the inverse exercise (bids from 2005 into 2008 and bids from 2009 into 2008, represented in Figure D.1 in Appendix D), so Combined Cycle bidding strategies are not causing this price deviation.

By comparing actual and synthetic prices, we can hypothesize two different patterns for the ex-post period, which covers the years 2009-2013. The first two years of the ex-post period (2009 and 2010, early ex-post) exhibit positive price differences (values over the zero line), in contrast with the last three years of the ex-post period (2011, 2012 and 2013, late ex-post), where both

FIGURE 4.8: Price differences (synthetic - actual) [EUR/MWh] with reference year 2008. Period 2002-2013.



Note: Dynamic Synthetic Scenario.
Source: Own simulations, hourly data from OMIE (2015b) (bids), REE (2002) - REE (2013) (technology identification) and CNMC (2015b) (monthly gas prices).

price differences are negative (values under the zero line), meaning that actual prices are higher than synthetic prices.[61] We will thoroughly analyze this effect subsequently in Section 4.4.2.

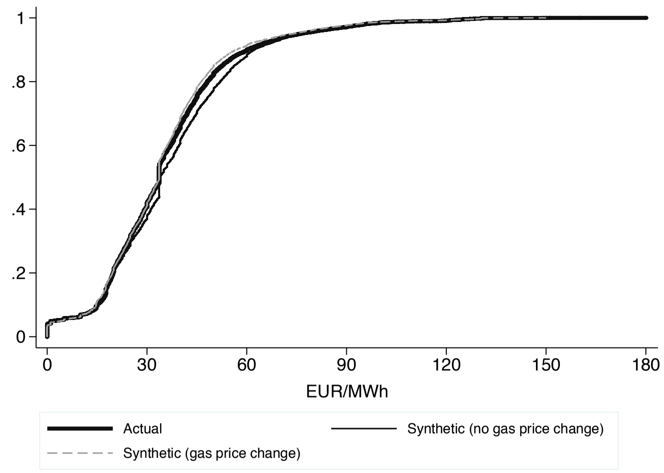
We next represent the Cumulative Distribution Function (CDF, hereafter) of actual and synthetic hourly prices for the period 2002-2013 in Figure 4.9. We cannot draw any conclusion from the CDF of the ex-ante period (Figure 4.9a), since actual and synthetic curves cross. However, concerning the ex-post period, we observe that synthetic CDFs are below actual CDF for the early ex-post (Figure 4.9b) and over actual CDF for the late ex-post (Figure 4.9c). Comparing ex-ante and ex-post periods, synthetic CDFs are closer to actual CDF in the ex-ante period than in the ex-post one.

Finally, Table 4.2 reports, for the Dynamic Synthetic Scenario, the descriptive statistics of the three time series: observed prices, synthetic prices based on original bids and synthetic prices including the change in gas price. Descriptive statistics for the Static Synthetic Scenario are presented in Appendix E (Table E.1). We observe that mean and median prices are higher during the ex-ante period than during the ex-post period. Concerning standard deviations, all price series seem to be more volatile during the ex-ante period than during the ex-post period. After conducting the skewness and kurtosis test for normality, we reject the hypothesis that hourly price series are normally distributed at the 1% level.

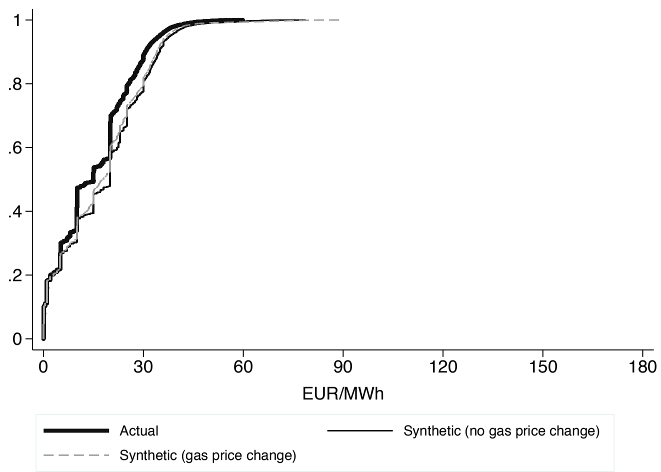
[61] The change of trend between the early ex-post and the late ex-post is visible after February 2011.

FIGURE 4.9: Cumulative distribution of actual hourly price series vs. synthetic price series.

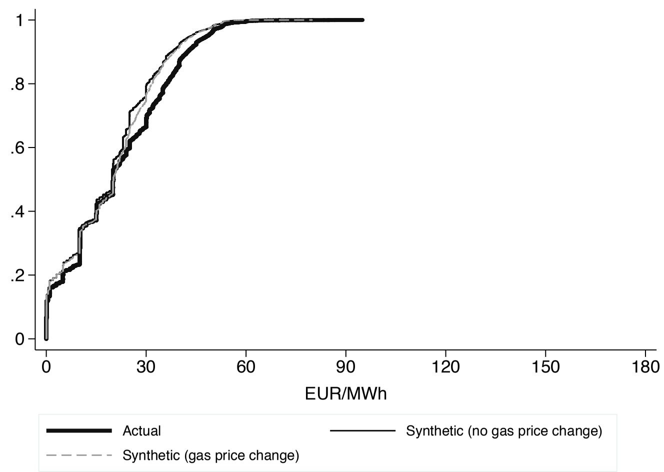
(A) Ex-ante 2002-2006



(B) Early ex-post: 2009-2010



(C) Late ex-post: 2011-2013



Source: Own simulations, hourly data from OMIE (2015b) (bids), REE (2002) - REE (2013) (technology identification) and CNMC (2015b) (monthly gas prices).

TABLE 4.2: Descriptive Statistics for actual and synthetic prices.

		Mean			Median			Standard Deviation			Skewness			Kurtosis		
		Actual	Synthetic (original)	Synthetic (gas price)	Actual	Synthetic (original)	Synthetic (gas price)	Actual	Synthetic (original)	Synthetic (gas price)	Actual	Synthetic (original)	Synthetic (gas price)	Actual	Synthetic (original)	Synthetic (gas price)
ex-ante	2002-2006	**33.86**	35.44	33.33	**32.01**	33.65	32.02	**19.43**	20.11	18.84	1.40	1.21	1.37	6.94	6.32	7.06
	2002	36.18	37.75	36.58	35.00	37.40	35.00	16.42	17.02	16.60	1.49	1.22	1.42	8.65	7.25	8.26
	2003	27.32	28.89	27.64	23.50	24.25	23.70	12.93	15.14	13.96	0.57	0.51	0.50	2.40	2.20	2.30
	2004	26.75	28.67	25.96	24.60	26.70	24.75	8.85	10.49	8.28	0.89	0.60	0.57	3.47	2.87	3.29
	2005	45.51	47.69	42.61	41.99	45.12	39.38	26.16	26.54	24.72	0.78	0.73	1.02	4.42	4.49	5.09
	2006	33.58	34.24	33.90	33.65	33.65	33.65	21.31	21.07	20.99	0.77	0.68	0.69	4.16	4.00	4.02
ex-post	2009-2013	**18.80**	18.50	18.62	**20.00**	20.00	20.00	**14.40**	13.62	13.77	0.50	0.35	0.38	2.55	2.50	2.71
	2009-2010	**15.10**	17.87	17.33	**15.00**	20.00	18.00	**11.58**	13.17	13.11	0.43	0.34	0.59	2.40	2.65	3.70
	2009	18.67	21.87	21.93	20.00	23.00	23.00	10.65	12.27	12.65	0.11	0.22	0.56	2.90	3.57	5.08
	2010	11.54	13.87	12.73	10.00	10.13	10.10	11.37	12.81	11.90	0.94	0.63	0.74	2.87	2.29	2.57
	2011-2013	**21.25**	18.92	19.47	**20.13**	20.00	20.13	**15.52**	13.89	14.12	0.34	0.34	0.25	2.27	2.41	2.25
	2011	23.76	22.24	22.44	22.00	22.00	22.00	15.13	14.04	14.10	0.20	0.22	0.20	1.97	2.34	2.33
	2012	23.04	19.35	20.39	25.00	20.00	22.07	15.03	13.26	13.79	-0.06	0.06	-0.04	1.88	2.05	1.95
	2013	16.96	15.15	15.59	15.13	15.00	15.00	15.49	13.43	13.58	0.95	0.76	0.62	3.66	3.23	2.78

Note: Dynamic Synthetic Scenario.
Source: Own simulations, hourly data from OMIE (2015b) (bids), REE (2002) - REE (2013) (technology identification) and CNMC (2015b) (monthly gas prices).

4.4.2 Has Renewable Energy induced more competitive behavior on Combined Cycle producers?

Table 4.3 presents the annual average price difference in EUR/MWh between synthetic and actual prices ($p_{synthetic} - p_{actual}$) for the Dynamic Synthetic Scenario. Positive price differences indicate that synthetic prices are higher than the observed ones (i.e. the market is more competitive after RES) and negative values show that synthetic prices are below (i.e. the market is less competitive after RES). All price differences in the ex-post period (2009-2013) are statistically significant at the 1% level. However, there are some price differences for the ex-ante period (2002-2006) which are not statistically significant.

The level of competitiveness is not constant over the years. Hence, we test the hypothesis that the market became more competitive after the massive introduction of RES in 2008. If that is so, the price differences in the period 2009-2013 would be positive and higher than in the period 2002-2006. Taking the Combined Cycle generators behavior in 2008 as the reference point, Table 4.3 part B (with actual gas prices) shows that in the period 2002-2006 (ex-ante), on average, the market behavior of Combined Cycle generators was less competitive than in 2008 (the price difference is -0.53, p-value=0.000), since the actual behavior of Combined Cycle gave rise to a price higher than the synthetic one. Similarly, Combined Cycle's behavior during the period 2009-2013 (ex-post) also seems to be less competitive on average than in 2008 (the price difference is -0.18, p-value=0.000). Thus, our benchmark scenario, year 2008, was competitive in relative terms.[62]

There are two distinct patterns in the ex-post years. On the one hand, during the early ex-post period (2009 and 2010) we detect positive price differences, indicating that the market became more competitive during the first years of massive renewable participation. At that time, Combine Cycle participants followed an *accommodating strategy*, with lower price bids in order to continue being matched in the pool. They could have reduced their bids to avoid being displaced from the pool by the new cheaper technologies (assuming that they were not already bidding at their marginal cost, but with a certain margin above it). This behavior is consistent with a less concentrated market after the introduction of RES.

On the other hand, during the late ex-post period (2011, 2012 and 2013) we observe negative price differences. In this case, the market was less competitive than in 2008 and Combined Cycles' *inhibition strategy* involved avoiding the matching in the day-ahead market. They submitted less energy at lower prices and more energy at higher prices, achieving a lower participation in the pool and increasing market prices. This means that since 2011 Combined Cycle

[62] Results for the ex-ante period are different when we observe part A (with original gas prices), where we note positive and significant price differences (1.58, p-value=0.000) that prevent us from extracting a conclusive result for the ex-ante period. Nonetheless, for the ex-post period we draw a consistent conclusion in both scenarios A and B: the market seems to be less competitive than in 2008 (-0.30 for part A and -0.18 for part B).

producers could have been bidding at higher prices than in the period where RES were not so active in the pool. One possible explanation for this behavior is that Combined Cycle plants may no longer be interested in being matched in the pool at the current prices. Rather, they could be bidding high to avoid being matched, and selling their electricity on secondary markets (e.g. intraday markets).[63]

Therefore, the low market prices corresponding to 2009 and 2010[64] could be due to a combination of two effects. First, the fact that there was more energy offered at lower prices (i.e. RES bid at zero price) reduced the electricity price by shifting the supply curve to the right. Second, the change of strategy of Combined Cycle plants, which are one of the marginal technologies at the pool and started lowering their price bids (accommodating strategy). On the contrary, the rise in electricity prices during the period 2011-2013 compared to 2009 and 2010 could be due to the inhibition strategy of gas producers. Combined Cycle producers were restricting the amount of energy they wanted to match in the pool by increasing their price bids. Therefore, market prices in 2011-2013 are higher than in 2009-2010, despite the fact that renewable participation kept increasing[65], which highlights the relevance of conventional producers' strategies on the electricity price formation.

Table 4.3 also shows the results by season and peak-hour. Seasonality plays an important role on the electricity market (demand of heating is higher in winter and demand for air-conditioning is higher in summer). However, there is no seasonal pattern in the differences between the synthetic and the actual prices.

Table 4.4 presents the percentage change in annual electricity prices. In this case, we use annual average prices, computed as the weighted average of hourly electricity prices for one year: $\frac{\sum_h^H p_h \cdot q_h}{\sum_h^H q_h}$, where p_h is the hourly electricity price, q_h is the hourly quantity traded and H is the total number of hours in the year in question. For both synthetic scenarios, we observe that price changes are lower if we consider the synthetic bids with the change in the gas price, which again suggests that Combined Cycle bidders adapt their bids according to fuel prices. Therefore, we focus the discussion on the results with change in gas prices, since they seem to reflect reality more accurately.

Comparing the ex-ante and ex-post periods in Table 4.4, we obtain that price changes in percentage terms are higher during the ex-post period. This confirms that Combined Cycle producers actually switched their strategies after the massive entry of RES, otherwise we would have obtained higher price variations also for the ex-ante period.

[63]In order to be allowed to participate on secondary markets, producers must bid up to capacity in the pool.
[64]We know from Ciarreta et al. (2014a), Chapter 2, that the weighted average annual price for 2008 was 65.55 EUR/MWh, for 2009 and 2010 was 38.01 EUR/MWh and for 2011-2013 was 50.80 EUR/MWh, 48.50 EUR/MWh and 44.26 EUR/MWh, respectively.
[65]According to Ciarreta et al. (2014a) (Chapter 2) in 2008 there was a 29% of RES in the pool and in 2013 there was more than 60%.

TABLE 4.3: Price differences (synthetic-actual) [EUR/MWh]. Dynamic Synthetic Scenario.

		synthetic - actual price (original gas price, A)						synthetic - actual price (with actual gas price, B)					
	year	all	summer	winter	peak	mid-peak	off-peak	all	summer	winter	peak	mid-peak	off-peak
ex-ante	2002-2006	1.58^{***}	2.12^{***}	1.03^{***}	1.63^{***}	1.62^{***}	1.48^{***}	-0.53^{***}	0.16^{***}	-1.23^{***}	-0.91^{***}	-0.92^{***}	0.42^{***}
	2002	1.57^{***}	1.69^{***}	1.43^{***}	1.89^{***}	1.82^{***}	-1.10^{***}	0.40^{***}	0.44^{***}	0.34^{***}	0.40^{***}	0.37^{***}	-1.58^{***}
	2003	1.57^{***}	2.06^{***}	1.07^{***}	1.75^{***}	1.86^{***}	0.96^{***}	0.32^{***}	0.69^{***}	-0.04	0.18^{**}	0.26^{***}	0.55^{***}
	2004	1.92^{***}	2.49^{***}	1.35^{***}	2.61^{***}	2.21^{***}	0.95^{***}	-0.79^{***}	-0.07^{*}	-1.51^{***}	-0.90^{***}	-1.17^{***}	-0.07
	2005	2.18^{***}	3.68^{***}	0.68^{***}	1.90^{***}	1.83^{***}	2.98^{***}	-2.90^{***}	-0.89^{***}	-4.91^{***}	-3.79^{***}	-4.08^{***}	-0.25^{***}
	2006	0.66^{***}	0.71^{***}	0.60^{***}	-0.01	0.37^{***}	1.62^{***}	0.32^{***}	0.64^{***}	-0.01	-0.45^{***}	-0.02	1.45^{***}
ex-post	2009-2013	-0.30^{***}	0.15^{***}	-0.75^{***}	1.16^{***}	0.81^{***}	-3.24^{***}	-0.18^{***}	0.40^{***}	-0.76^{***}	1.30^{***}	0.95^{***}	-3.18^{***}
	2009-2010	2.77^{***}	3.29^{***}	2.24^{***}	3.14^{***}	3.33^{***}	1.53^{***}	2.23^{***}	2.62^{***}	1.83^{***}	2.57^{***}	2.73^{***}	1.11^{***}
	2009	3.20^{***}	3.32^{***}	3.08^{***}	3.28^{***}	3.55^{***}	2.56^{***}	3.26^{***}	3.26^{***}	3.26^{***}	3.43^{***}	3.65^{***}	2.47^{***}
	2010	2.33^{***}	3.26^{***}	1.40^{***}	3.01^{***}	3.12^{***}	0.49^{***}	1.19^{***}	1.98^{***}	0.40^{***}	1.70^{***}	1.82^{***}	-0.26^{***}
	2011-2013	-2.33^{***}	-1.93^{***}	-2.75^{***}	-0.18^{***}	-0.87^{***}	-6.40^{***}	-1.78^{***}	-1.07^{***}	-2.49^{***}	0.45^{***}	-0.24^{***}	-6.02^{***}
	2011	-1.52^{***}	-1.08^{***}	-1.95^{***}	0.82^{***}	0.26^{***}	-6.24^{***}	-1.32^{***}	-0.69^{***}	-1.95^{***}	1.03^{***}	0.46^{***}	-6.06^{***}
	2012	-3.69^{***}	-3.35^{***}	-4.03^{***}	-1.71^{***}	-2.14^{***}	-7.76^{***}	-2.65^{***}	-1.94^{***}	-3.35^{***}	-0.50^{***}	-0.96^{***}	-7.09^{***}
	2013	-1.81^{***}	-1.36^{***}	-2.25^{***}	0.38^{***}	-0.74^{***}	-5.19^{***}	-1.37^{***}	-0.59^{***}	-2.16^{***}	0.83^{***}	-0.22^{***}	-4.91^{***}

Dynamic Synthetic Scenario: Reference year = 2008, Target year (ex-ante) = 2002-2006, Target year (ex-post) = 2009-2013.
We represent: $p_{synthetic} - p_{actual}$.
*** price differences statistically significant at 1%, ** price differences statistically significant at 5%, * price differences statistically significant at 10%. Source: Own simulations, hourly data from OMIE (2015b) (bids), REE (2002) - REE (2013) (technology identification) and CNMC (2015b) (monthly gas prices).

Table 4.4: Percentage change in annual market prices [%].

	ex-ante					ex-post				
						early ex-post		late ex-post		
	2002	2003	2004	2005	2006	2009	2010	2011	2012	2013
Dynamic Synthetic Scenario										
Original bids	4%	6%	8%	4%	2%	17%	21%	-4%	-14%	-9%
With actual gas price	1%	1%	-3%	-7%	1%	17%	11%	-4%	-10%	-6%
Static Synthetic Scenario										
Original bids	-2%	-3%	-5%	-7%	-3%	-21%	-16%	7%	23%	13%
With actual gas price	-1%	-1%	-1%	0%	-1%	-14%	-10%	3%	13%	5%

Dynamic Synthetic Scenario: Reference year = 2008, Target year (ex-ante) = 2002-2006, Target year (ex-post) = 2009-2013.
Static Synthetic Scenario: Reference year (ex-ante) = 2002-2006, Reference year (ex-post) = 2009-2013, Target year = 2008.
We represent: $\frac{p_{synthetic}-p_{actual}}{p_{actual}}$ in %. Source: Own simulations, hourly data from OMIE (2015b) (bids), REE (2002) - REE (2013) (technology identification) and CNMC (2015b) (monthly gas prices).

For the ex-post period in the Dynamic Synthetic Scenario (Table 4.4), synthetic electricity prices are higher than actual prices (17% for 2009 and 11% for 2010) in the first two years (early ex-post period). On the contrary, during the late ex-post period we observe that synthetic prices are lower than actual prices (-4% for 2011, -10% for 2012 and -6% for 2013).

Observing the Static Synthetic Scenario in Table 4.4, we detect the same phenomenon, supporting the hypothesis that Combined Cycle plants could have evolved in their bidding strategies after the introduction of RES. Furthermore, price changes in the ex-ante period for the Static Synthetic Scenario are even lower than in the Dynamic Synthetic Scenario and they are of similar magnitude in the ex-post period.[66] The discrepancy in percentages is explained by the fact that the demand in the reference and target years is different and also the elasticities. Thus, the same change in bids generates a different variation depending on the elasticity of demand.

Concerning the energy traded on the spot market, Table 4.5 represents the annual share of electricity from Combined Cycle plants that was matched in the pool for the period 2002-2013 ($\frac{q_{CC}}{q_{total}}$ in %.). We compare actual with synthetic shares for both counterfactual scenarios, for the synthetic price series based on original bids and including the change in gas prices. As we observe again in Table 4.4, synthetic values built from prices that incorporate fuel prices are closer to actual results. Additionally, the percentage of electricity from Combined Cycle sources matched in the ex-ante period is very similar to actual shares. As was the case with market prices, we detect differences in the traded quantities for the early and late ex-post periods. For the years 2009-2010, the share of energy from Combined Cycle units in the Dynamic Synthetic Scenario is lower than actual values, and higher for the Static Synthetic Scenario. In contrast, for the period 2011-2013 we observe higher electricity shares for the Dynamic Synthetic Scenario

[66] All the price differences are statistically significant at 1%.

TABLE 4.5: Share of annual quantity traded from Combined Cycle plants [%].

	ex-ante						ex-post				
							early ex-post		late ex-post		
	2002	2003	2004	2005	2006	2008	2009	2010	2011	2012	2013
Dynamic Syntethic Scenario											
Actual bids	3%	7%	11%	19%	24%	-	31%	26%	30%	25%	24%
Original bids	2%	5%	9%	17%	24%	-	27%	24%	32%	29%	26%
With actual gas price	3%	7%	12%	21%	24%	-	27%	25%	31%	28%	25%
Static Synthetic Scenario											
Actual bids	-	-	-	-	-	32%	-	-	-	-	-
Original bids	32%	33%	33%	33%	33%	-	37%	36%	31%	27%	29%
With actual gas price	32%	32%	32%	32%	32%	-	36%	35%	32%	29%	31%

Dynamic Synthetic Scenario: Reference year = 2008, Target year (ex-ante) = 2002-2006, Target year (ex-post) = 2009-2013.
Static Synthetic Scenario: Reference year (ex-ante) = 2002-2006, Reference year (ex-post) = 2009-2013, Target year = 2008.
We represent: $\frac{q_{CC}}{q_{total}}$ in %. Source: Own simulations, hourly data from OMIE (2015b) (bids), REE (2002) - REE (2013) (technology identification) and CNMC (2015b) (monthly gas prices).

and lower values for the Static Synthetic Scenario. This means that Combined Cycle units have been delivering higher energy shares in the ex-ante period and lower shares during the ex-post period. This is consistent with gas plants submitting bids at higher prices during the last years of the analysis, which had the effect of increasing electricity prices and reducing their matched energy.

Summing up the results in this section, we find empirical evidence of two different strategies. In the first one, the *accommodating strategy*, Combined Cycle units bid at lower prices in order to ease their matching on the spot market. This behavior can be observed during 2009 and 2010 and is consistent with the hypothesis that firms would react to a less concentrated market with more competitive strategies. During this period, Combined Cycle producers seem to accommodate in the pool and try to minimize the impact that RES production was causing on electricity prices. In the second one, the *inhibition strategy*, some of the Combined Cycle generators started submitting higher price bids during the period 2010-2013, in order to avoid their participation on the spot market. This had the effect of reducing their quantity of energy traded in the pool and electricity prices rose.[67]

4.4.3 Sensitivity analysis

In order to see whether our results are due to some specific characteristics of 2008, which is the reference year we used, we have conducted the same simulations for the year 2012 using

[67]According to Ciarreta et al. (2014a) (Chapter 2) weighted average annual prices for 2009 and 2010 were 38.01 EUR/MWh and for 2011-2013 they were 50.80 EUR/MWh, 48.50 EUR/MWh and 44.26 EUR/MWh, respectively.

2005 as the new reference year. We obtained a price reduction of 6% when we introduced 2005 Combined Cycle bids (considering the gas price pass-through) into 2012 and a 28% share of Combined Cycle over total energy traded in the pool. Both values are in line with the 10% price decrease and the 28% share of Combined Cycle production obtained using 2008 as the reference year, which indicates that our findings are robust.

4.5 Conclusions and Policy Implications

The outburst of Renewable Energy on electricity markets in the last decade is undeniable. Its direct effect on electricity prices has been an issue addressed in many papers. However, additional indirect effects on the strategy of other market participants still remained largely unexplored.

In this chapter we test the hypothesis that the market became more competitive after the introduction of RES, due to less market concentration after the entry of renewable producers. In order to do it, we explore the evolution of Combined Cycle bidding strategies in the Spanish pool during the period 2002-2013.

We construct synthetic supply curves and we observe how electricity prices would have evolved if these synthetic bidding had taken place. Our synthetic bids are based on the behavior of Combined Cycle producers at a time where Renewable Energy was taking off but most of the Combined Cycle capacity was already installed. Therefore, these synthetic strategies reflect the bidding behavior facing low rates of RES. We set that moment in the year 2008 and we divide our target period in an ex-ante period from 2002 to 2006 (less RES in the market) and an ex-post period from 2009 to 2013 (more RES in the market).

We analyze two different synthetic scenarios based on the reference year 2008. In the Dynamic Synthetic Scenario we take actual bids of Combined Cycle generators of the reference year to replace the bids of the year of analysis (e.g. we substitute the bids of 2012 with the bids of 2008). In the Static Synthetic Scenario we take actual bids of Combined Cycle generators of the target years to replace the bids of the reference year (e.g. we substitute the bids of 2008 with the bids of 2012). Additionally, we build two different supply curves for each synthetic scenario. In the first case we use the original bids from Combined Cycle producers of the reference year, whereas in the second one we add the change in gas prices to the synthetic bids. Therefore, if gas prices in the reference year are higher (lower) than in the target year, synthetic bids will be higher (lower) than actual bids in the reference year.

Once we have our synthetic supply curves, we compute hourly electricity prices for the period 2002-2013 and we compare them with actual hourly prices. If synthetic electricity prices are higher than actual values after RES entered the market, we conclude that Combined Cycle producers would now be bidding at lower prices as a consequence of RES participation. On the contrary, if synthetic prices are lower than actual ones, Combined Cycle units would now be submitting higher price bids. The lower bidding strategy would be consistent with our hypothesis of a more competitive environment.

Our simulations show that Combined Cycle plants certainly evolved after large participation of RES on the electricity market. There have been important changes in bidding prices after 2009 (ex-post period), whereas strategic variations until 2006 (ex-ante period) were much smaller. Furthermore, we identified two different strategies in the ex-post period. In the accommodating strategy, applied during 2009 and 2010 (early ex-post), Combined Cycle units bid at lower prices in order to guarantee their matching on the spot market. In the inhibition strategy, however, some of the Combined Cycle generators started submitting higher price bids during the period 2010-2013 (late ex-post), in order to avoid their participation on the spot market. The accommodating strategy seems to be consistent with the hypothesis that firms would react to a less concentrated market with more competitive strategies. On the contrary, the inhibition strategy corresponds to a period where market conditions (i.e. lower prices caused by RES participation) make the pool less attractive to Combined Cycle producers. As a result, the share of energy traded by Combined Cycle plants in the pool decreased in recent years. We also conclude that there is a pass-through of natural gas prices into electricity bids.

All in all, the participation of RES on the Spanish electricity market not only led to a decrease in equilibrium prices, but it also caused a change in Combined Cycle bidding strategy on the spot market. The fact that Combined Cycle units are bidding at higher prices since 2011 should be taken into account in the merit order effect analysis of RES.

An interesting question that is left for further research is whether market price reductions entailed by RES are sufficient to compensate for the increasing costs of the adjustment markets. Finally, another interesting question would be to detect structural changes in bidding strategies thorough a time series analysis of actual and synthetic electricity prices.

Chapter 5

Pricing policies for efficient Demand Side Management in Spain

5.1 Introduction

In electricity systems where there is great penetration of intermittent renewable generation, the supply of reserve capacity has proven inappropriate to keep an efficient balance in the system, due to its high maintenance costs (Strbac, 2008). However, some recent studies (Freeman, 2005; Conchado and Linares, 2009; Cappers et al., 2011; Finn and Fitzpatrick, 2014) suggest that the application of pricing policies directed to Demand Side Management (DSM, hereafter) might help the penetration of renewable sources[68] and contribute to improving the technical efficiency of electricity systems, thus restricting their economic costs, since part of the consumption would shift to hours where generation, transport and distribution may be performed more efficiently.

DSM presents therefore a high potential for improving technical efficiency in electricity systems. Many of the analyses that are centered on energy efficiency have already set their focus on the design of systems and pricing policies aimed at achieving an efficient DSM. According to existing literature the inelasticity of electricity demand is caused largely by the absence of a price signal to the final consumers (Ilic et al., 2002; Lijesen, 2007). Whereas the wholesale market price, set on an hourly basis, clearly reflects the changes in marginal costs on the supply side (electricity production), the fact that prices for final consumers are kept invariable provokes a chronic excess (or lack) of consumption compared to the efficient level, thus generating an important market failure (Borenstein and Holland, 2005; Jessoe and Rapson, 2013).

[68]The intermittence of many renewable technologies (e.g. wind or solar) can interfere with the technical efficiency of electricity grids. This problem could be reduced by energy storage systems (currently not available or very expensive) or by the use of DSM strategies. They have the double effect of reducing electricity consumption and allowing flexibility in the grid management. This helps the penetration of renewable sources in systems with DSM by establishing a better match between demand and supply, including the variations of renewable sources (Pina et al., 2012).

This disparity between wholesale and retail price has traditionally been a major cause of economic inefficiency on electricity markets. Given the regulation where retail prices are independent from the consumption time frame, many final consumers have not perceived the correct price signal, causing inefficient electricity consumption that affects all participants in the electricity system. On the one hand, electricity companies have found it impossible to optimize their capacity and load factors. On the other hand, consumers themselves have not managed to reduce the variable part of their electricity bill.

DSM policies therefore consist of a redistribution of load over time, shifting consumption from periods of high demand (peak demand) to other periods of lower demand (off-peak demand). DSM policies do not necessarily reduce total energy consumption, although some policies may, according to their design, also involve a reduction in electricity demand and not only a shift in consumption. The key element in DSM is the incentive aimed at final consumers to modify their electricity usage habits. This incentive is usually translated to the variable part of the electricity tariff and may be achieved through smart meters, because they allow users to monitor, control and predict their electricity consumption.

International analyses have already proven that, when consumers have access to information on their consumption, they react to dynamic pricing policies by a reduction of electricity consumption at peak hours. In fact, one study by Faruqui and George (2005) applied to the Californian market concludes that the necessary investments to completely replace conventional meters with smart meters could be fully offset by the demand response benefits. Moreover, according to the COM (2014c), smart metering systems in the European Union are expected to deliver an overall benefit per customer of 309 euros for electricity along with energy savings of 3%.

This chapter addresses DSM in Spain and a main challenge is the lack of data on consumer response to changing prices. The literature referring to residential electricity demand in Spain is scarce and it has principally focused on corroborating the inelasticity of the demand owing to the absence of price signals (Blázquez et al., 2013; Labandeira et al., 2012), without analyzing the effect of a variable pricing system.

In this regard, it is worth mentioning the growing penetration of smart meters in the Spanish market, where it is expected that by year 2018 all the electricity meters for consumers with less than 15 kW of contracted power will be new.[69] Since July 2015, the electricity price for retail consumers is based on the result of the pool (the wholesale market auction). Thus, consumers who have an operating smart meter in their homes may already participate actively in the efficient DSM, because their electricity price is linked to the pool on an hourly basis (which

[69]Order ITC/3860/2007, BOE (2007b), and Order IET/290/2012, BOE (2012d) The deployment of smart meters in Spain started in 2011. The roll-out plan is to have 35% installed by the end of 2014, 70% by the end of 2016 and 100% by 2018 (COM, 2014c).

partly solves the price signal transmission problem). Hence, the results of this analysis may turn out to be significant for the future evolution of the Spanish electricity market.

Therefore, based on the grounds of international experience on electricity markets, we here propose a procedure to calculate optimal prices for retail consumers in Spain, by comparing them with actual prices. We develop a theoretical model based on time of use pricing and simulate optimal hourly prices in the current demand conditions for different elasticity values.

In our model, the price paid for electricity by the residential consumer is linked to the daily market price and varies according to the proposed pricing scheme. Since the wholesale market price is set on an hourly basis, if a sufficient amount of consumers modified their consumption pattern from peak (higher production costs) to off-peak (lower production costs) periods, the aggregate load curve would change, thereby leading to significant savings for the whole electricity system. Our results show that, if elasticity is not too low, it is possible to transmit the price signal to consumers, who will then modify their consumption pattern.

We present a model that considers consumer behavior not only concerning the substitution between peak and off-peak hours in response to different prices (short-term elasticities, e.g. one hour) but also the possibility that consumers have to switch between retailers depending on the price scheme they offer (medium-term elasticities, e.g. one month), which is linked to the switching costs (the higher the switching costs the lower the elasticity to switch retailer). If consumers are sensitive to other retailers' offers, they may react to prices resulting in lower costs for them. We work with two elasticities associated to retailers. First, the retail price elasticity reflects the disposal of consumers to switch retailer if their current retailer changes prices. Second, the inter-retailer price elasticity is related to the willingness to change retailer if the rival retailer changes prices.

The chapter is divided into seven sections. Given the importance of the latest regulatory changes that directly affect retail consumer prices, we start in Section 5.2 with an analysis of the regulatory framework concerning retail electricity pricing in Spain. In Section 5.3, we describe the main existing rates in international markets, including hourly differentiation for residential consumers, and we highlight the most important findings of the literature on dynamic pricing, by analyzing both the elasticity of demand and the international experience in the implementation of time-of-use pricing. The description of our theoretical model is presented in Section 5.4. Sections 5.5 and 5.6 describe the data we use to perform the simulations and the results obtained, respectively. Finally, Section 5.7 details the main conclusions of our analysis and directions for further research.

5.2 Regulatory framework

Consumers may choose a regulated price (PVPC[70]) or the market price.[71] In the absence of an explicit request by the consumer, the contracting modality with the reference retailer is always the PVPC. In the case of consumers with a regulated price, the average hourly price (P_h) is calculated as the weighted average of the daily market price (P_h^D) with the quantity traded in the daily market (Q_h^D) and the price resulting from the different sessions of the intraday market (P_h^i) with the quantity traded in the intraday markets (Q_h^i):[72]

$$P_h = \frac{P_h^D Q_h^D + \sum_{i \epsilon I} P_h^i Q_h^i}{Q_h^D + \sum_{i \epsilon I} Q_h^i}$$

Therefore, the final cost of electricity purchase for the p billing period (FC_p), which includes H hours, would be the sum of the wholesale market price, together with the prices of the corresponding sessions of the intraday market, the costs of the adjustment services and capacity payments, as well as the access costs (fixed by the regulator). Thus, the cost of production is determined as a weighted average of the average hourly price (P_h), adjustment services costs ($AS_{p,h}$) and the loss coefficients ($LOSS_{p,h}$).

$$FC_p = \frac{\sum_{h=1}^{H} ((P_h + AS_{p,h})(1 + LOSS_{p,h}))Q_{p,h}}{\sum_{h=1}^{H} Q_{p,h}}$$

According to the CNMC (2014d), the new system presents important advantages with respect to the former one. Firstly, the risk premium of the forward market is not transferred to final consumers. Secondly, the price setting mechanism conveys a much less distorted signal of the value of electricity than before. Finally, it facilitates the implementation of efficient mechanisms for DSM. However, it is not free of disadvantages, with the main one being that despite the prices being known ex-ante by the consumers, so that they may anticipate their consumption decisions, they are not yet readily accessible to all of them (due to the lack of smart meters) and it is complicated in many cases to make an efficient consumption adaptation to these new prices.[73] Furthermore, there is price variability for the final consumer.

[70] In 2014 CESUR auctions were eliminated and the Royal Decree 216/2014, of 28 March, established a new calculation methodology for the so-called Voluntary Price for the Small Consumer (*Precio Voluntario para el Pequeño Consumidor*, PVPC) and its legal contracting system, in force since July 2015. The PVPC, which came into force on 1 April 2014, determines the maximum prices that the benchmark retailers may charge to consumers that select that price option (see Article 17 of Law 21/2013, BOE (2013d)).

[71] The percentage of consumers under a regulated price has reduced from 70% in June 2012 to 60% in June 2013 (CNMC, 2014f).

[72] Article 10 of Royal Decree 216/2014.

[73] The tariff for consumers without smart metering is obtained according to bimonthly averages calculated using consumption patterns (Royal Decree 216/2014, BOE (2014a).)

5.3 Theoretical background and literature review

We here conduct a review of the recent literature about the elasticity of demand in dynamic pricing for residential electricity consumption. Triggered by the lack of data at the national level, the goal is to find reference values to be used in the Section 5.5 simulations, where (i) to calculate electricity prices, we apply the elasticity values from field studies of other countries (presented in Section 5.3.1) and (ii) once we obtain prices, we compare them with international values (presented in Section 5.3.2).

5.3.1 Electricity pricing

The main systems of DSM comprise two types of programs: price-oriented or incentive-oriented. In the price-oriented systems, consumers react to the different price schemes, modifying their consumption patterns according to the electricity price. In the incentive-oriented systems, however, consumers receive a compensation if they reduce their consumption in a given period. Some of those within existing dynamic pricing programs are highlighted in Appendix F: Time of Use (ToU), Critical Peak Pricing (CPP), Critical Peak Rebate (CPR), Inclining Block Rates (IBR) and Real-Time Pricing (RTP).

Our analysis focuses exclusively on price-oriented policies, which evolve both in terms of design complexity and in flexibility to the consumer as we progress from static pricing (without hourly differentiation) to real-time pricing (maximum differentiation). We here model a ToU design for two periods (peak vs. off-peak). RTP (further research) are the last step in dynamic pricing, since they provide the consumer with the greatest flexibility to adapt their consumption.

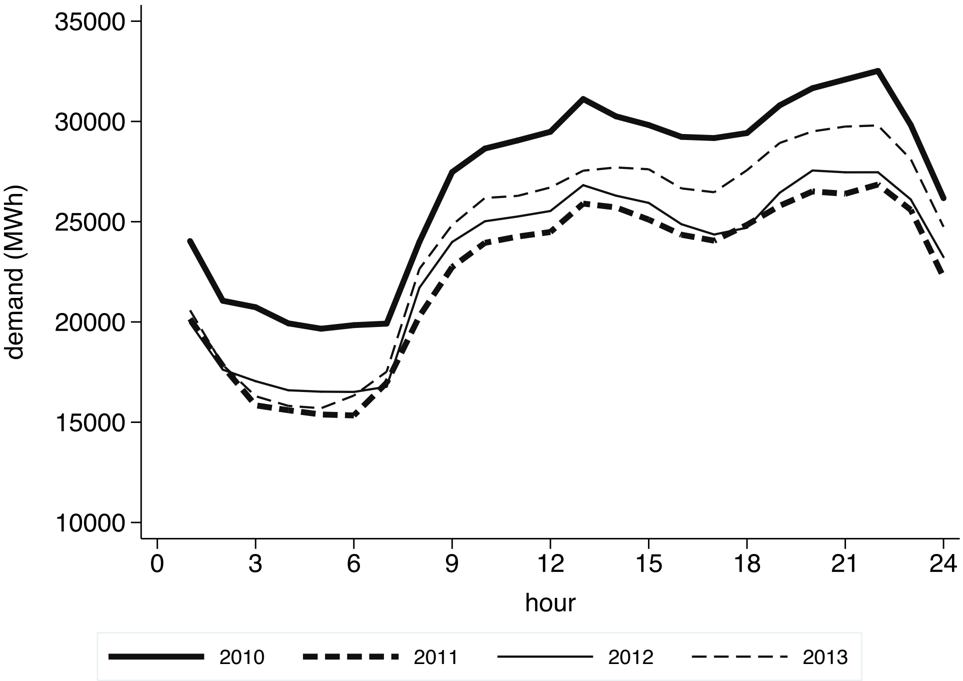
5.3.2 Inter-hour price elasticity

The electricity demand presents some very clear patterns throughout the 24 hours of the day. There are a series of hours, the so-called peak hours, where electricity consumption is higher. On the contrary, other off-peak periods exist where the demand of electricity is considerably lower. Figure 5.1 represents the distribution of electricity demand in Spain for the period 2010-2013. For every year, we plot the demand for a representative day in winter (the third Wednesday of December) in Figure 5.1a, and another representative day in summer (the third Wednesday of June) in Figure 5.1b.

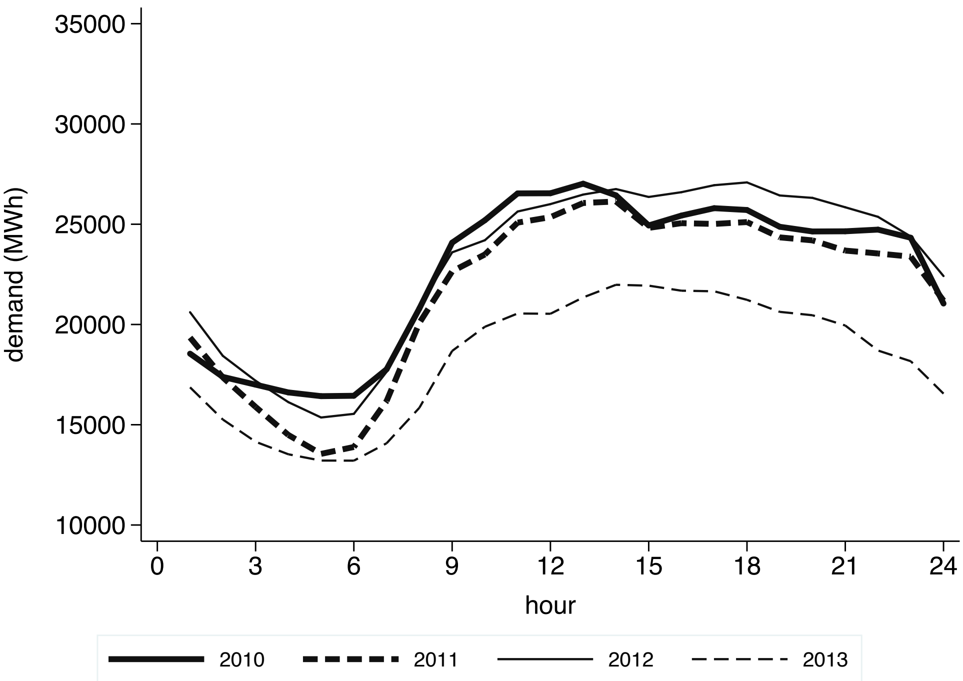
Demand patterns for the winter and summer seasons are different but consistent across years. In winter demand is generally higher (compared to summer, 19% higher on average for 2010, 3% for 2011, 0% for 2012 and 32% for 2013) and presents two differentiated peaks (at around 13:00h and 22:00h). In contrast, the demand in summer is lower than in winter and shows a

FIGURE 5.1: Evolution of electricity demand in Spain [MWh]. Period 2010-2013.

(A) Winter



(B) Summer



Note: Third Wednesday of December for winter and third Wednesday of June for summer.
Source: Own elaboration, data from OMIE (2015b).

single peak (at around 12:00h-14:00h), which can occasionally be longer than the peak-time in winter (peaks are smoother in summer). The effect of the economic crisis is also clear in Figure 5.1, which results in a reduced demand level in recent years (note that the highest demand occurs in 2010 for both winter and summer).

Considering this variable pattern of electricity demand, there is scope for analyses based on a shift of consumption from peak to off-peak hours. The most solid argument for this transfer of consumption is the price elasticity of demand, which shows the responsiveness of the electricity demand to a change in its price. In fact, the success of any ToU pricing policy (including RTP) lies in the price elasticity of demand (Fillipini, 1995a). In the analyses of DSM, three types of elasticities are employed: own-price, cross-price, and substitution (Conchado and Linares, 2010). First, the own-price elasticity expresses the percentage variation of the electricity demand during a given period to a variation of 1% in the price of electricity during the same period (i.e. $\frac{\partial q_i}{\partial p_i}\frac{p_i}{q_i}$). Second, the cross-price elasticity represents the percentage change of the electricity demand during a given period i to a change of 1% in the price of another different period j (i.e. $\frac{\partial q_i}{\partial p_j}\frac{p_j}{q_i}$). Finally, the elasticity of substitution expresses the relative demand $\frac{q_j}{q_i}$ shift from a peak (off-peak) period to an off-peak (peak) period subsequent to a variation of 1% in the relative price $\frac{p_i}{p_j}$ (i.e. $\frac{\partial(q_j/q_i)}{\partial(p_i/p_j)}\frac{p_i}{p_j}\frac{q_j}{q_i}$).

King and Chatterjee (2003), after reviewing the estimations of elasticities in 35 studies in US and other countries under ToU and CPP for domestic customers and small businesses between 1980 and 2003, conclude that the average own-price elasticity is -0.3, where values oscillate between -0.1 and -0.8 (between -0.1 and -0.4 for most studies). However, Faruqui and George (2002) estimate average values of 0.14, on a range between 0.07 and 0.21, for the elasticity of substitution.

We distinguish between own-price elasticity, cross-price elasticity and elasticity of substitution, as well as between short-run elasticity and long-run elasticity. According to a study by Filippini (2011), short-run own-price elasticity for the Swiss market is lower than 1%, whereas it is higher than 1% in the long run. Thus, the demand in terms of short-run own-price elasticity is inelastic, whereas it is more elastic in the long-run. Additionally, they find positive short-run and long-run cross-price elasticities in all their models, and this means that peak and off-peak electricity are always substitutes.

As far as Spain is concerned, not many empirical studies have yet been conducted on the elasticity of residential electricity demand (and none of them related to dynamic pricing). In Blázquez et al. (2013), using econometric techniques based on household income, weather and geographical location, among others, the own-price elasticity values are -0.07 and -0.19 in the short- and long-run, respectively, for the time period 2000-2008. These numbers are lower than the ones presented in the studies mentioned above, but the results in the long-run (with somewhat higher elasticities) leave the door open for the effectiveness of dynamic pricing policies.

Labandeira et al. (2006, 2012) also analyze the elasticity of residential demand in Spain, for the time period 1975-1995, and they obtain values which are around the average of the rest of the studies, providing an own-price elasticity of -0.78.

Table 5.1 shows a summary of estimated elasticities for residential consumers in some international studies.

Table 5.1: Studies on the price elasticity of demand for retail consumers

Source	Country	Type of program	Type of elasticity	Value
Filippini (1995b)	Switzerland	ToU	own-price	peak: -0.60; off-peak: -0.79
Aubin et al. (1995)	France	CPP	own-price	peak: -0.79; off-peak: -0.18
Al Faris (2002)	Saudi Arabia United Arab Emirates Kuwait, Oman, Bahrain y Qatar	ToU	own-price	short-run: range from -0.04 to -0.18 long-run: range from -0.82 to -1.39
Faruqui and George (2002)	US	ToU	substitution (peak for off-peak)	0.14 on average (range from 0.07 to 0.21)
King and Chatterjee (2003)	US and others	ToU/CPP	own-price	-0.3 on average (range from -0.1 to -0.8)
Associates (2005)	California	CPP	substitution (peak for off-peak)	0.09 on average (range from 0.04 to 0.13)
Consulting (2005)	Illinois	RTP (one day forward)	own-price	-0.08 on average (range from -0.05 to -0.12)
Labandeira et al. (2006)	Spain	-	own-price cross-price	-0.78 0.05
Blázquez et al. (2013)	Spain	-	own-price	short-run: -0.07 long-run: -0.19

Source: Own elaboration.

5.3.3 Elasticity in the presence of retailer competition

Since the liberalization of the electricity market in Spain in 2009, consumers are allowed to switch to a competitor once their time commitment is over. However, even when the two firms' products are identical, consumers perceive costs for switching from one firm to another. According to Klemperer (1995), these switching costs "give firms a degree of market power over their repeat-purchasers, and mean that firms' current market shares are important determinants of their future profits". In this sense, each firm faces a trade-off between (i) charging a lower price that attracts new consumers who will stay with them during the following periods (they invest in market share), and (ii) charging higher prices to their existing consumers that capitalize on (they harvest profits now at the expense of losing market share in the future). As a consequence, switching costs results in higher prices and welfare losses for consumers. They may also discourage new entry and then diminish market competitiveness. Finally, switching costs reduces the incentives for firms to differentiate their products.

There is a wide range of literature exploring the effects of switching costs on telecommunications. However, due to the recent deregulation of electricity markets, literature on switching costs in the electricity retail sector is still scarce and focuses mainly on the factors affecting household decisions to switch to another electricity supplier (Ek and Söderholm, 2008; Yang, 2014). Ilieva and S.A. (2014) investigate the effects of regulation in the Nordic retail market for electricity, and they conclude that decisions made by one retailer have a strong impact on the market strategy of the other. They model retail competition but they do not consider the effect of inter-hour price elasticities (the change of consumption between peak and off-peak periods). In this regard, there are no estimations of elasticities related to the rival's prices. As far as we are concerned, we are the first authors to model electricity prices depending on both switching costs and inter-hour price elasticities, in an attempt to understand the effect of retail competition in the cost of electricity.

5.3.4 International experience

Table 5.2 shows a summary with the results of some of the pilot programs on dynamic pricing to residential consumers in different countries. All the programs achieved a reduction of electricity demand, with it being lower for the ToU programs (e.g. Ireland) and higher for the CPP programs (e.g. Sweden). Additionally, load shifting is also achieved with ToU pilots (e.g. United Kingdom). A more detailed analysis of the international experience is presented in Appendix G.

5.4 The model

We apply a Bertrand competition model with differentiated products and switching costs in order to define the optimal prices that a retailing company could apply to residential consumers under ToU pricing. Differentiation is provided by the billing services of the retailer, which may not be identical.

Switching costs refer to the cost that consumers face when they switch retailers. These costs appear due to the fact that the retailing company, when setting hourly prices, must take into account that customers operating with them in this period (e.g. this month, this quarter, this year ...) could switch to a competitor for the next period (e.g. following month, following quarter, following year ...), if the other company's prices are better adapted to their needs.

Table 5.2: Results of pilot programs on dynamic pricing policies for retail consumers

Source	Country	Type of program	Year	Results
Hierzinger et al. (2013)	Germany	ToU	Since 2008	-
Hierzinger et al. (2013)	France	ToU+CPP	Since 1994	∇ demand: 15%-45%
Darby and McKenna (2012); Di Cosmo et al. (2012)	Ireland	ToU	2009-2010	∇ demand: 2.5%-8.8%
Torriti (2012)	Italy	ToU	Since 2010	Δ demand: 13%
Hierzinger et al. (2013)	Norway	ToU	2005-2008	∇ demand: 24.5%
Vesterberg et al. (2014); Lindskoug (2006)	Sweden	CPP	2003/2004-2005/2006	∇ demand: 50%
Breukers and R.M. (2013)	United Kingdom	ToU	2007-2010	Load shift: 10%
Faruqui et al. (2010); Faruqui and Sergici (2010)	US/Canada	ToU	-	Average ∇ demand: 7%
Allcott (2011)	US(Chicago)	RTP	Since 2003	∇ peak demand: 5%-14%

Source: Own elaboration.

For instance, a customer with high electric consumption in peak hours and little propensity to shift it to off-peak hours would prefer a company offering moderate prices for peak hours, even though the price during off-peak hours is higher. Furthermore, this customer would be willing to switch retailer if the competitor's price scheme outweighs the switching costs.

Taking into account these considerations, we pose and solve the Bertrand problem with differentiated products and exogenous switching costs. We present the optimal ToU price scheme in two periods and the generalization to H daily periods (e.g. if $H = 24$, then 1 period = 1 hour). Despite the existence of different types of dynamic pricing, we consider that ToU is a suitable scheme, given the great variety of existing worldwide field experiments (most of the studies presented in Appendix G deal with ToU pricing). On the one hand, we can simulate ToU pricing using the available data on elasticities. On the other hand, the results of the implemented pilot programs provide a benchmark to compare our results with.

5.4.1 ToU pricing in two periods

We consider two symmetric retailers (A and B), two periods (t and $t+1$), and two intervals, peak and off-peak. Subindex 1 refers to peak hours and subindex 2 to off-peak hours. Consumers buying from a retailer in period t have to wait until period $t+1$ to change retailer. There is a peak and an off-peak interval during period t and a peak and an off-peak interval during period $t+1$; consumers distribute their electricity consumption between these two intervals.

Firms A and B decide their pricing schemes simultaneously and non-cooperatively, considering that consumers allocate their electricity consumption in period t based on peak and off-peak prices, and that consumers can switch retailer in period $t+1$ depending on the pricing of both firms. Our two-firm model with symmetry can be easily generalized to the case of a larger number of competitors.

We assume the same utility function as in Singh and Vives (1984) for the representative consumer and we generalize it. Thus, our utility function takes the general form $U(q_i, q_j) = \eta_i q_i + \eta_j q_j - \frac{\omega_i q_j^2 + (\gamma_i + \gamma_j) q_i q_j + \omega_j q_j^2}{2}$, which is quadratic and strictly concave. Consumers maximize net utility $U(q_i, q_j) - \sum_{k=i,j} p_k q_k$, giving rise to a linear demand structure, where q_k is the amount of good k and p_k its price. Letting $\theta = \omega_i \omega_j - \gamma_i \gamma_j$, $a_i = \frac{\eta_i \omega_j - \eta_j \gamma_i}{\theta}$, $b_i = \frac{\omega_j}{\theta}$ and $c_i = \frac{\gamma_i}{\theta}$ for $i \neq j$, demands are:

$$q_i = a_i - b_i p_i + c_i p_j$$
$$q_j = a_j - b_j p_j + c_j p_i,$$

where $a_i, b_i, c_i > 0$ and $b_i > c_i$.

We have multiproduct firms, where the goods are peak and off-peak hours, in this market. Additionally, we consider two different periods t and $t+1$. It takes one period to switch retailers and thus consumers cannot switch retailer until the end of the period t (period $t+1$). Therefore, the demand functions for firm A and period t for peak (subindex 1) and off-peak (subindex 2) hours are:

$$\begin{aligned} q_{A1}(t) &= a_1 - b_1 p_{A1} + b_{12} p_{A2} \quad \text{(peak)} \\ q_{A2}(t) &= a_2 - b_2 p_{A2} + b_{21} p_{A1} \quad \text{(off- peak)}, \end{aligned}$$

where $a_i, b_i, b_{ij} > 0$.

That is, the demand in peak hours for retailer A depends only on the own peak and off-peak price. Prices are assumed to be constant over time so that index t is omitted for notational convenience.

However, consumers may switch retailer in period $t+1$, so that the demand functions for firm A and period $t+1$ for peak and off-peak hours, respectively, are:

$$\begin{aligned} q_{A1}(t+1) &= A_1 - B_1 p_{A1} + B_{12} p_{A2} + D_1 p_{B1} + D_{12} p_{B2} \quad \text{(peak)} \\ q_{A2}(t+1) &= A_2 - B_2 p_{A2} + B_{21} p_{A1} + D_2 p_{B2} + D_{21} p_{B1} \quad \text{(off-peak)}, \end{aligned}$$

where $A_i, B_i, B_{ij}, D_i, D_{ij} > 0$.

The last two terms represent the competitor's prices in the previous period. In this setting, firm A could lose customers in $t+1$ if p_{A1} were too high or if p_{B1} were too low in t.[74]

[74] Demand in t also depends on the rivals' prices in $t-1$, but those terms are constant at t and therefore included in a_1 and a_2.

Since we assume that both firms A and B are identical, by symmetry, the demand functions for firm B and periods t and $t+1$ for peak (subindex 1) and off-peak (subindex 2) hours are:

$$\begin{aligned}
q_{B1}(t) &= a_1 - b_1 p_{B1} + b_{12} p_{B2} \quad \text{(peak)} \\
q_{B2}(t) &= a_2 - b_2 p_{B2} + b_{21} p_{B1} \quad \text{(off-peak)} \\
q_{B1}(t+1) &= A_1 - B_1 p_{B1} + B_{12} p_{B2} + D_1 p_{A1} + D_{12} p_{A2} \quad \text{(peak)} \\
q_{B2}(t+1) &= A_2 - B_2 p_{B2} + B_{21} p_{B1} + D_2 p_{A2} + D_{21} p_{A1} \quad \text{(off-peak)}
\end{aligned}$$

We define the parameters of the model as positive and we classify them into two groups: (i) a_1, b_1, b_{12} and a_2, b_2, b_{21} refer to the hourly electricity demand in t and they are closely related to the hourly price elasticity of demand, and (ii) A_1, B_1, B_{12}, D_1, D_{12} and A_2, B_2, D_{21}, D_2, D_{21} refer to the consumer reaction in $t+1$ to the price of the rival firm, and they are linked to the retailer switching rate. In Section 5.5 we will assign different values to these parameters to carry out the simulations, since none of them are directly observable.

Firms maximize their profits[75] and their decision variables are peak and off-peak prices. Therefore, the maximization functions for A and B, respectively, are:

$$\begin{aligned}
\pi_A &= (p_{A1} - c_1)[q_{A1}(t) + q_{A1}(t+1)] + (p_{A2} - c_2)[q_{A2}(t) + q_{A2}(t+1)] \\
\pi_B &= (p_{B1} - c_1)[q_{B1}(t) + q_{B1}(t+1)] + (p_{B2} - c_2)[q_{B2}(t) + q_{B2}(t+1)]
\end{aligned}$$

The parameters c_1 and c_2 are the unit costs for the retailing companies, the same for firms A and B and for periods t and $t+1$: c_1 are the unit costs in the peak hours, which correspond to the average price of the pool during the peak period, and c_2 are the unit costs in the off-peak hours, which reflect the average price of the pool during the off-peak period.

Firm A chooses the prices p_{A1} and p_{A2} so as to maximize its profits (symmetric for firm B):

$$\max_{\{p_{A1}, p_{A2}\}} (p_{A1} - c_1)[(\alpha_1 - \beta_1 p_{A1} + \beta_{12} p_{A2}) + D_1 p_{B1} + D_{12} p_{B2})] + (p_{A2} - c_2)[(\alpha_2 - \beta_2 p_{A2} + \beta_{21} p_{A1}) + D_2 p_{B2} + D_{21} p_{B1})],$$

where $\alpha_i = a_i + A_i$, $\beta_i = b_i + B_i$ and $\beta_{ij} = b_{ij} + B_{ij}$ for $i = 1, 2$, $j = 1, 2$ and $i \neq j$.

[75] We assume that they do not discount future payoffs or $\frac{1}{1+r} = 1$, being r the interest rate.

Solving the first order conditions for both firms A and B, we get the following reaction functions for firms A and B for peak and off-peak periods:

$$p_{A1} = \frac{\alpha_1 + \beta_1 c_1 - \beta_{21} c_2 + (\beta_{12} + \beta_{21}) p_{A2} + D_1 p_{B1} + D_{12} p_{B2}}{2\beta_1}$$

$$p_{A2} = \frac{\alpha_2 + \beta_2 c_2 - \beta_{12} c_1 + (\beta_{12} + \beta_{21}) p_{A1} + D_2 p_{B2} + D_{21} p_{B1}}{2\beta_2}$$

$$p_{B1} = \frac{\alpha_1 + \beta_1 c_1 - \beta_{21} c_2 + (\beta_{12} + \beta_{21}) p_{B2} + D_1 p_{A1} + D_{12} p_{A2}}{2\beta_1}$$

$$p_{B2} = \frac{\alpha_2 + \beta_2 c_2 - \beta_{12} c_1 + (\beta_{12} + \beta_{21}) p_{B1} + D_2 p_{A2} + D_{21} p_{A1}}{2\beta_2}$$

From these equations, note that in each period the price in the peak and off-peak periods (both the own price and the price of the other firm) is affected by the electricity production costs and consumer behavior regarding switching consumption between retailers (parameters A_1, B_1, B_{12}, D_1, D_{12}, A_2, B_2, B_{21}, D_2 and D_{21}) and between peak and off-peak periods (parameters a_1, b_1, b_{12}, a_2, b_2 and b_{21}).

By symmetry, we have that $p_{A1} = p_{B1}$ and $p_{A2} = p_{B2}$, so we get the Nash equilibrium (Equations 5.1 and 5.2) for the peak and off-peak prices:

$$p_{A1} = p_{B1} = \frac{(2\beta_2 - D_2)(\alpha_1 + \beta_1 c_1 - \beta_{21} c_2) + (\beta_{12} + \beta_{21} + D_{12})(\alpha_2 + \beta_2 c_2 - \beta_{12} c_1)}{(2\beta_1 - D_1)(2\beta_2 - D_2) - (\beta_{12} + \beta_{21} + D_{12})(\beta_{12} + \beta_{21} + D_{21})} \tag{5.1}$$

$$p_{A2} = p_{B2} = \frac{(2\beta_1 - D_1)(\alpha_2 + \beta_2 c_2 - \beta_{12} c_1) + (\beta_{12} + \beta_{21} + D_{21})(\alpha_1 + \beta_1 c_1 - \beta_{21} c_2)}{(2\beta_1 - D_1)(2\beta_2 - D_2) - (\beta_{12} + \beta_{21} + D_{12})(\beta_{12} + \beta_{21} + D_{21})} \tag{5.2}$$

It is worth noting that the price in each period (peak vs. off-peak) increases with the own cost and decreases with the cost of the other period. Likewise note that the cross-price elasticity (parameters β_{12} and β_{21}) should be relatively low, in order to guarantee positive prices.

5.4.2 ToU pricing in H períodos

Following the same approach as in the previous subsection, the general rule for the reaction functions for H periods is:

$$p_{Ai} = \frac{\alpha_i + \beta_i c_i - \sum_{j \neq i}^{H} \beta_{ji} c_j + \sum_{j \neq i}^{H} (\beta_{ij} + \beta_{ji}) p_{Aj} + D_i p_{Bi} + \sum_{j \neq i}^{H} D_{ij} p_{Bj}}{2\beta_i} \tag{5.3}$$

where $\alpha_i = a_i + A_i$, $\beta_i = b_i + B_i$ and $\beta_{ij} = b_{ij} + B_{ij}$ for $i = 1 \ldots H$. In the case of 24-hour periods, we would have $H = 24$.

However, for the sake of simplicity, the analysis will be presented for two periods, peak and off-peak. Lack of data prevents us from extending the simulations to $H = 24$ periods.

5.5 Simulations and data

5.5.1 General purpose of the simulations

The main goal of our simulations is to illustrate how the optimal prices depend on the parameters of the model and provide their numerical values according to the theoretical model set up in Section 5.4. We compare these values with real prices at both national and international levels, to check their validity, and we observe the effect of the elasticity parameters in our model. In order to carry out the simulations, the parameters of the model related to the consumers' elasticity between hours and their willingness to switch retailer, as well as the costs of electricity production need to be calibrated. To this end, we employ real data from the Spanish electricity system provided by the market operator (OMIE)[76], the system operator (REE)[77] and the National Energy Commission (CNMC)[78], along with results from other studies on inter-hour price elasticity (see Section 5.3) and the costs of switching retailers.

Simulations are applied to the ToU model with two periods. For the sake of simplicity, and in order to compare the results with a benchmark scenario (actual prices), we simulate two different situations: one representative month from the winter period and one representative month from the summer period. The chosen months are January and June 2013.

5.5.2 Data on the cost of electricity for retailers

We assume that the cost of electricity for a retailer in each period is the final electricity price reported by OMIE. This price includes the day-ahead market, intraday markets, adjustment services and capacity payments, similarly to what is already being considered to set the current regulated consumer price (PVPC, see Section 5.2). The cost of production for generators is actually different according to each technology (higher for conventional fossil fuels, and lower for renewables). For the scenario of 24 different time intervals, the cost for a retailer would coincide with the final price of each hour. We consider one representative hour for each period and we simulate prices for that hour for two-tier ToU prices. We simulate the peak prices for hour 13 and the off-peak prices for hour 4, hours that correspond to a maximum and a minimum price spike, respectively, for both winter and summer (see Figure 5.1). The idea behind choosing one representative hour for each period and not averages is to observe the shift in consumption

[76] Operador del Mercado Ibérico de Electricidad.
[77] Red Eléctrica de España.
[78] Comisión Nacional de los Mercados y la Competencia, the former Comisión Nacional de la Energía (CNE).

that would occur if consumers reacted to different prices according to the time-frame. The hourly selection for the different periods in our ToU pricing scheme is made according to the official data provided by the CNMC (see Table 5.3).

TABLE 5.3: Hourly distribution of ToU pricing in Spain

Price schedule	Winter			Summer		
	Peak	Valley	Off-peak	Peak	Valley	Off-peak
Two periods	from 12h to 21h	-	from 22h to 11h	from 13h to 22h	-	from 23h to 12h
Three periods	from 13h to 22h	from 7h to 12h and from 23h to 00h	from 1h to 6h	from 13h to 22h	from 7h to 12h and from 23h to 00h	from 1h to 6h

Note: The change from wintertime to summertime and vice versa coincides with the official dates for time change.
Source: Billing data from CNMC (BOE, 2014c).

5.5.3 Data on the inter-hour price elasticity

Given the absence of estimations of elasticities for Spain, we employ own- and cross-price elasticities obtained by Faruqui and George (2002) for peak, valley and off-peak periods (see Matrix 5.4).

$$\epsilon_{ToU2} = \begin{bmatrix} \epsilon_{11} & \epsilon_{12} \\ \epsilon_{21} & \epsilon_{22} \end{bmatrix} = \begin{bmatrix} -0.25 & 0.05 \\ 0.10 & -0.20 \end{bmatrix} \tag{5.4}$$

These values come from actual pricing experiments with ToU rates that were conducted in the United States, and represent possible responses of retail customers if they could perceive the price signal. Additionally, these elasticities are included into the average ranges provided by the literature (-0.1 and -0.8, see Section 5.3 for more detail), so they are a useful starting point for the discussion on the effect of elasticities. Matrix 5.4 presents the selected elasticity values for the ToU pricing in two periods: peak and off-peak. Note that own-price demand elasticities are much higher than cross-price demand elasticities and that customers seem to be more elastic regarding peak periods compared to off-peak periods. Finally, it can be noted that the values for cross-price elasticities approach the 0.05 reported by Labandeira et al. (2006).[79] Therefore, we assume that all these figures could be applied to the Spanish case.

Thus, once we know one point of the demand curve $\epsilon_{ii}\epsilon_{ij}$, a pair price-quantity (q_i, p_i)[80], and given the values for own- and cross-price elasticities, we may calculate the parameters of the model related to the shift in consumption between hours using the following definitions:[81]

[79] The only available data for Spain.
[80] Concerning quantities, we consider that 25% of the aggregate demand corresponds to the residential sector, as reported by IDAE (2011).
[81] Subindex i and j refer to different hours.

Own-price elasticities:

$$\epsilon_{ii} = \frac{\partial q_i}{\partial p_i}\frac{p_i}{q_i} = -b_i\frac{p_i}{q_i} \tag{5.5}$$

Cross-price elasticities:

$$\epsilon_{ij} = \frac{\partial q_i}{\partial p_j}\frac{p_j}{q_i} = b_{ij}\frac{p_j}{q_i} \tag{5.6}$$

Finally, the parameter a_i is considered to represent the maximum amount of energy demanded in period t for each hour, that is, the energy that is asked at zero price in the hourly aggregate demand curve.

5.5.4 Data on the switching rate

According to the CNMC (2015a), the annual switching rate in the retail electricity market is defined as the ratio between the number of customer switching among energy utilities in one year and the total number of consumers in that year. Switching supplier is the action through which a customer changes his/her supplier, that is, the meter point associated with a household must be re-registered with a different supplier. Customers switching residence but remaining with their previous supplier are not recorded and changes resulting from a merger are also excluded. Table 5.4 displays the evolution of the switching rate in Spain from 2009 to 2013. The first column represents the switching rate for all electricity consumers (domestic, small firms and industrial), whereas the second column shows the switching rate for the domestic sector, which includes small domestic consumers with and without hourly discrimination, big domestic consumers with and without hourly discrimination and small businesses with and without hourly discrimination.

Table 5.4: Switching rate in the Spanish retail electricity market [%]

Year	All Consumers	Domestic consumers
2009	5.23%	4.39%
2010	7.42%	6.61%
2011	10.61%	10.04%
2012	12.07%	11.63%
2013	12.97%	12.57%

Source: CNMC (2015a) and own elaboration.

Table 5.4 shows that, even almost without any price signal at all, Spanish consumers have reacted to the difference in prices between retailers with an increasing rate of change (4.39% in 2009 vs. 12.57% in 2013) since the liberalization of the retail electricity market in 2009.[82] Thus,

[82] In Europe, only Spain, the Netherlands, Ireland and Norway have switching rates higher than 10% (CNMC, 2015c).

we take these values as a minimum reaction for the simulations, because the ratio may be even higher in a more appropriate scenario. Of course, price is not the only variable that consumers evaluate when they reflect upon a possible change of retailer, since other behavioral parameters associated to the customer's profile are also present (willingness to change, attachment to the current supplying company, income etc.), and even within those customers for which the price is relevant, differences exist according to their concern for the environment or their own comfort. In this regard, according to an empirical study carried out in Switzerland (Sütterlin et al., 2011), at least 54.57% of residential customers would adapt their consumption according to retailer prices if there were targeted communication strategies.

Concerning retailers' price elasticities, in a paper by Ilieva and S.A. (2014) based on the Norwegian retail market, the authors consider that consumers react to changes in prices with an elasticity of -0.4, whereas the elasticity facing price changes of other retailers is 0.3. Therefore, our baseline values for elasticities on retail pricing are -0.4 (own retailer's price for the same period i, E_{lili}) and 0.3 (rival retailer's price, or inter-retailer price, for the same period i, E_{liki}). We employ these numbers to compute the coefficients B_1, B_2, D_1 and D_2 and analyze the effect of different elasticity values on prices, consumption and costs for retail consumers. In the simulations we always hold own retailer price elasticities higher than inter-retailer price elasticities, since the elasticity of demand to other retailer prices is lower due to the switching costs. Finally, for the sake of simplicity in the simulations, we assume that the effect of inter-hour cross-price elasticities when choosing retailer (i.e. own retailer's and other retailer's price in off-peak hours when choosing consumption for peak hours and vice versa) is negligible.[83] We then assume that B_{12}, B_{21}, D_{12} and D_{21} are zero. The following expressions characterize the computation of the parameters related to the own retailer and the competitor in the baseline scenario (l and k refer to firms, A or B; whereas i and j refer to periods, peak or off-peak):

Retailer price elasticities for one period related to the same period (peak or off-peak):

$$\mathrm{E}_{lili} = \mathrm{E}_{li} = -0.4 = \frac{\partial q_{li}}{\partial p_{li}} \frac{p_{li}}{q_{li}} = -B_i \frac{p_{li}}{q_{li}} \tag{5.7}$$

Inter-retailer price elasticities for one period related to the same period (peak or off-peak):

$$\mathrm{E}_{liki} = \mathrm{E}_{lki} = 0.3 = \frac{\partial q_{li}}{\partial p_{ki}} \frac{p_{ki}}{q_{li}} = D_i \frac{p_{ki}}{q_{li}} \tag{5.8}$$

Retailer price elasticities for one period (peak or off-peak) related to the other period (off-peak or peak):

$$\mathrm{E}_{lilj} = 0 = \frac{\partial q_{li}}{\partial p_{lj}} \frac{p_{lj}}{q_{li}} = B_{ij} \frac{p_{lj}}{q_{li}} \tag{5.9}$$

[83] Taylor et al. (2005) found that cross-price elasticities are generally an order of magnitude smaller than own-price effects. Furthermore, Borenstein and Holland (2005) and Holland and E.T. (2006) assume that cross-price elasticities between demands in different periods are zero.

Inter-retailer price elasticities for one period (peak or off-peak) related to the other period (off-peak or peak):

$$\mathrm{E}_{likj} = 0 = \frac{\partial q_{li}}{\partial p_{kj}} \frac{p_{kj}}{q_{li}} = D_{ij} \frac{p_{kj}}{q_{li}} \tag{5.10}$$

For the sake of simplicity in the notation, we rename the elasticities of Equations 5.7 and 5.8 as E_{li} and E_{lki}. In a model with two firms (A and B) and two periods (1=peak and 2=off-peak), assuming that consumers do not react to inter-hour retailer prices, the elasticities for the simulations are:

- Retailer price elasticities:
  - For firm A and peak period: E_{A1}.
  - For firm A and off-peak period: E_{A2}.
  - For firm B and peak period: E_{B1}.
  - For firm B and off-peak period: E_{B2}.
- Inter-retailer price elasticities:
  - For firm A and peak period: E_{AB1}.
  - For firm A and off-peak period: E_{AB2}.
  - For firm B and peak period: E_{BA1}.
  - For firm B and off-peak period: E_{BA2}.

In summary, using Equations 5.5-5.6 and 5.7-5.10 we determine starting values for the simulations according to the existing literature. On the one hand, we settle empirical figures for hour and inter-hour price elasticities (parameters a_i, b_i, b_{ij}). On the other hand, we define baseline values for retailer and inter-retailer price elasticities (parameters A_i, B_i, B_{ij}, D_i and D_{ij}).

5.6 Results and Discussion

We here present the results of the simulations on the optimal prices based on our theoretical model. We analyze the effect of different consumers' profiles concerning their willingness to switch retailer while keeping the inter-hour price elasticities fixed. In this regard, we define the following scenarios:

- Benchmark: Actual regulated electricity prices applied in Spain for the reported period (observed prices).

- Simulations:
  - Baseline: Based on the elasticities on switching rate from Ilieva and S.A. (2014) (see Section 5.5.4).
  - Scenario 1: Consumers switch energy retailers easily. Switching costs are low.
  - Scenario 2: Consumers find it difficult to switch energy retailers. Switching costs are high.
  - Scenario 3: Consumers switch energy retailers depending on peak prices: They are more sensitive to peak prices.
  - Scenario 4: Consumers switch energy retailers depending on off-peak prices: They are more sensitive to off-peak prices.

5.6.1 Simulations for ToU in two periods

We select some of the feasible[84] combinations of retailer price elasticities as an example for this section. As stated in Section 5.5, if Spanish domestic consumers are switching retailers at a 12.57% rate with almost no information on prices and energy usage, it can be assumed that for each retailer, price elasticities could be higher than the baseline in the scenarios with price signal transmission.

We simulate the following scenarios for firm A:

- Baseline: Literature values from Ilieva and S.A. (2014): $\mathrm{E}_{A1} = \mathrm{E}_{A2} = -0.4$, $\mathrm{E}_{AB1} = \mathrm{E}_{AB2} = 0.3$.
- Scenario 1: $\mathrm{E}_{A1} = \mathrm{E}_{A2} = -2.0$, $\mathrm{E}_{AB1} = \mathrm{E}_{AB2} = 1.8$.
- Scenario 2: $\mathrm{E}_{A1} = \mathrm{E}_{A2} = 0$, $\mathrm{E}_{AB1} = \mathrm{E}_{AB2} = 0$.
- Scenario 3: $\mathrm{E}_{A1} = -2.0, \mathrm{E}_{A2} = -1.0$, $\mathrm{E}_{AB1} = 1.8, \mathrm{E}_{AB2} = 0.9$.
- Scenario 4: $\mathrm{E}_{A1} = -1.0, \mathrm{E}_{A2} = -2.0$, $\mathrm{E}_{AB1} = 0.9, \mathrm{E}_{AB2} = 1.8$.

Once we have assigned reference values for the elasticities on retailer switching under different scenarios we start with the evaluation of the effect of inter-hour price elasticities (peak vs. off-peak hours). Tables 5.5 and 5.6 show optimal prices based on our model for ToU pricing in two periods: peak vs. off-peak, for winter and summer, respectively. In this case, we use the inter-hour elasticities from Faruqui and George (2002) (see Section 5.5.3) for all the simulated scenarios. In Tables 5.7-5.10 we evaluate the effect of higher inter-hour price elasticities.

[84] This means that we restrict prices and quantities to be positive.

Table 5.5: Price simulations according to Time of Use. Two periods: peak vs. off-peak. Winter

	Price [EUR/kWh]			Price Ratio	Difference peak - off-peak	Total Revenue	Δ Consumption	Δ Efficiency
	all	peak	off-peak	peak/off-peak	[MWh]	[kEUR]	[%]	[%]
Benchmark	0.150938	-	-	-	-	207	-	-
	-	0.183228	0.063770	2.87	2,976	187	-	-
Baseline	0.230720	0.266546	0.176423	1.51	2,765	311	-1.48	-66.55
Scenario 1	0.110342	0.134668	0.076305	1.76	2,309	153	1.35	18.06
Scenario 2	0.529217	0.577583	0.462066	1.25	3,144	1023	41.17	-447.42
Scenario 3	0.124283	0.136683	0.108805	1.26	1,600	180	5.85	3.61
Scenario 4	0.142811	0.182925	0.078711	2.32	3,406	211	8.07	-13.09

Note: Winter refer to January 2013 and summer to June 2013. Peak refer to hour 13 and off-peak to hour 4.
Source: Own elaboration, actual regulated tariff from CNMC (2014e) and data for the simulations from OMIE (2015b).

Table 5.6: Price simulations according to Time of Use. Two periods: peak vs. off-peak. Summer

	Price [EUR/kWh]			Price Ratio	Difference peak - off-peak	Total Revenue	Δ Consumption	Δ Efficiency
	all	peak	off-peak	peak/off-peak	[MWh]	[kEUR]	[%]	[%]
Benchmark	0.138658	-	-	-	-	175	-	-
	-	0.167658	0.057190	2.93	2,179	154	-	-
Baseline	0.217202	0.231021	0.196896	1.17	2,353	269	-1.81	-74.86
Scenario 1	0.104187	0.115676	0.088137	1.31	2,092	132	0.21	14.40
Scenario 2	0.498198	0.499421	0.496517	1.01	2,779	877	39.62	-470.29
Scenario 3	0.120643	0.117581	0.124438	0.94	1,415	159	4.84	-3.70
Scenario 4	0.131629	0.157607	0.090437	1.74	3,052	177	6.89	-15.36

Note: Winter refer to January 2013 and summer to June 2013. Peak refer to hour 13 and off-peak to hour 4.
Source: Own elaboration, actual regulated tariff from CNMC (2014e) and data for the simulations from OMIE (2015b).

We note the important effect of the model parameters from the results in Tables 5.5 and 5.6. For instance, the assumption of very low elasticity for the change of retailer in Scenario 2 makes the prices set by the retailer considerably higher than in the other scenarios, but assuming that consumers do not present elasticity at all to the prices of retail companies is a very unlikely premise (mainly because there has been an increasing switching rate in Spain after 2009, see Table 5.4, which confirms that consumers react to retailer prices). We observe this effect for both seasons, being prices higher in winter than in summer (benchmark prices are also higher for winter and we observe this effect for all the scenarios). On the contrary, in Scenario 1, where consumer switch between retailers easily, we obtain the lowest prices and consumption increments of 1.35% in winter and 0.25% in summer. The reduction of the peak/off-peak ratio translates into efficiency improvements for consumers of 18.06% for winter and 14.40% for summer.

In Scenario 4, where residential customers switch energy retailers depending on the hourly tariff (more sensitive to off-peak prices), we obtain the closest results to the benchmark prices of the regulated tariff with two differentiated periods (this again is the case for both winter and summer). This makes sense, because consumers up to now were not able to manage their consumption between hours in the event of a change in prices, which meant that prices did not have to be necessarily set in a way to encourage a shift in consumption. However, in Scenario 3, we found a reduction of the consumption difference between peak and off-peak hours with respect to the benchmark. In this way, the price signal is transferred to the final residential customers, so they may modify their consumption pattern to make it coincide with periods where the system is underused. Total costs for consumers are also lower and we observe an increase of 5.85% of consumption in winter and 4.84% in summer, which indicates that ToU pricing does not necessarily achieve consumption reductios and could only induce consumption shifts.

As regards the Baseline scenario (the one using the elasticities found in the literature), it is the only case that achieves a reduction in consumption (-1.48% in winter and -1.81% in summer), but costs for consumers are higher than with the regulated tariff (prices are higher).

Finally, if we compare our prices with those presented in Section 5.3.4 and Appendix G, referring to international experience, we observe that our peak/off-peak ratio is lower than the benchmark in all our scenarios. Additionally, the scenarios showing the lowest cost for consumer and the greater peak shaving (Scenarios 1 and 3, with peak prices between 1.26 and 1.76 times higher than off-peak ones for winter and between and 0.94 and 1.31 for summer), quite resemble those in Germany (1.28-1.67, depending on the price schedule) and Italy (1.41). Despite the different pricing level between countries (higher for Germany and lower for Italy), the ratios between them and our results tend to remain steady.

In Tables 5.5 and 5.6 we observed the effect of different retailer and inter-retailer price elasticities, but we held inter-hour price elasticities constant. However, inter-hour elasticities is another important factor for demand pricing. Tables 5.7-5.10 report the results of the simulations for higher inter-hour elasticities than in Tables 5.5 and 5.6 (20% higher in Tables 5.7 and 5.8 and 60% higher in Tables 5.9 and 5.10).[85] We observe that when consumer demand is more elastic to inter-hour prices, the costs for consumers and the peak/off-peak ratio reduce for all the scenarios.

[85]We increase the four values of elasticity (ϵ_{11}, ϵ_{12}, ϵ_{22} and ϵ_{21}) by the same rate.

Table 5.7: Price simulations according to Time of Use. Two periods: peak vs. off-peak. Winter. Elasticity 20% than in Faruqui and George (2002).

	Price [EUR/kWh]			Price Ratio	Difference peak - off-peak	Total Revenue	Δ Consumption	Δ Efficiency
	all	peak	off-peak	peak/off-peak	[MWh]	[kEUR]	[%]	[%]
Benchmark	0.150938	-	-	-	-	207	-	-
	-	0.183228	0.063770	2.87	2,976	187	-	-
Baseline	0.358870	0.248784	0.166554	1.49	2,825	299	1.11	-60.06
Scenario 1	0.185423	0.131806	0.075268	1.75	2,347	151	2.05	19.03
Scenario 2	0.766336	0.487219	0.387556	1.26	3,143	861	41.17	-360.81
Scenario 3	0.218420	0.133974	0.105449	1.27	1,615	177	6.66	5.21
Scenario 4	0.223868	0.175442	0.077800	2.26	3,469	206	8.89	-10.09

Note: Winter refer to January 2013 and summer to June 2013. Peak refer to hour 13 and off-peak to hour 4. Source: Own elaboration, actual regulated tariff from CNMC (2014e) and data for the simulations from OMIE (2015b).

Table 5.8: Price simulations according to Time of Use. Two periods: peak vs. off-peak. Summer. Elasticity 20% than in Faruqui and George (2002).

	Price [EUR/kWh]			Price Ratio	Difference peak - off-peak	Total Revenue	Δ Consumption	Δ Efficiency
	all	peak	off-peak	peak/off-peak	[MWh]	[kEUR]	[%]	[%]
Benchmark	0.138658	-	-	-	-	175	-	-
	-	0.167658	0.057190	2.93	2,179	154	-	-
Baseline	0.342116	0.215576	0.185720	1.16	2,407	258	0.76	-68.09
Scenario 1	0.175272	0.113226	0.086895	1.30	2,122	130	0.92	15.39
Scenario 2	0.724649	0.421199	0.417301	1.01	2,779	738	39.62	-380.27
Scenario 3	0.212520	0.115269	0.120544	0.96	1,424	157	5.66	-1.90
Scenario 4	0.207232	0.151156	0.089318	1.69	3,105	173	7.73	-12.44

Note: Winter refer to January 2013 and summer to June 2013. Peak refer to hour 13 and off-peak to hour 4. Source: Own elaboration, actual regulated tariff from CNMC (2014e) and data for the simulations from OMIE (2015b).

Table 5.9: Price simulations according to Time of Use. Two periods: peak vs. off-peak. Winter. Elasticity 60% than in Faruqui and George (2002).

	Price [EUR/kWh]			Price Ratio	Difference peak - off-peak	Total Revenue	Δ Consumption	Δ Efficiency
	all	peak	off-peak	peak/off-peak	[MWh]	[kEUR]	[%]	[%]
Benchmark	0.150938	-	-	-	-	207	-	-
	-	0.183228	0.063770	2.87	2,976	187	-	-
Baseline	0.320181	0.220542	0.149834	1.47	2,902	277	5.35	-48.45
Scenario 1	0.178505	0.126591	0.073250	1.73	2,412	148	3.36	20.89
Scenario 2	0.586309	0.374264	0.294418	1.27	3,144	659	41.17	-252.56
Scenario 3	0.208509	0.128941	0.099466	1.30	1,646	172	8.16	8.20
Scenario 4	0.209648	0.162733	0.075889	2.14	3,565	196	10.36	-4.76

Note: Winter refer to January 2013 and summer to June 2013. Peak refer to hour 13 and off-peak to hour 4. Source: Own elaboration, actual regulated tariff from CNMC (2014e) and data for the simulations from OMIE (2015b).

Table 5.10: Price simulations according to Time of Use. Two periods: peak vs. off-peak. Summer. Elasticity 60% than in Faruqui and George (2002).

	Price [EUR/kWh]			Price Ratio	Difference peak - off-peak	Total Revenue	Δ Consumption	Δ Efficiency
	all	peak	off-peak	peak/off-peak	[MWh]	[kEUR]	[%]	[%]
Benchmark	0.138658	-	-	-	-	175	-	-
	-	0.167658	0.057190	2.93	2,179	154	-	-
Baseline	0.305243	0.190985	0.167012	1.14	2,481	240	-3.40	-55.94
Scenario 1	0.168856	0.108751	0.084508	1.29	2,175	127	-5.88	17.29
Scenario 2	0.554871	0.323421	0.318280	1.02	2,779	565	28.53	-267.75
Scenario 3	0.202605	0.110954	0.113644	0.98	1,447	152	-1.36	1.47
Scenario 4	0.194523	0.140186	0.087035	1.61	3,184	165	0.55	-7.24

Note: Winter refer to January 2013 and summer to June 2013. Peak refer to hour 13 and off-peak to hour 4. Source: Own elaboration, actual regulated tariff from CNMC (2014e) and data for the simulations from OMIE (2015b).

5.7 Conclusions and Policy Implications

In a context with a growing presence of intermittent renewable energy, this chapter deals with the design of electricity prices for final residential consumers. A key element to improve the technical efficiency of the electricity system is the design of pricing policies that reflect actual generation costs. In this regard, prices with hourly differentiation serve a dual purpose. On the one hand, they allow the costs of the system to be managed in a more efficient way, by incorporating differences in prices which are positively correlated with cost variations. On the other hand, this difference in prices facilitate Demand Side Management and encourages customers to change their behavior, which again contributes to improving the efficiency of the system by shifting consumption from hours where generation is more costly to other periods where it is less expensive. This chapter sheds light on the functioning of the retail market in Spain, combining theoretical models with simulations based on real data. The highlight of our chapter is a model that considers both the effect of inter-hour energy usage and the price that retailers set. If consumers are shown to be sensitive to other retailer prices, this has the effect of achieving lower prices. Analyzing the reaction of residential consumers with respect to price changes may give the policy makers important information on the potential for regulation of residential energy prices.

The empirical work consisted in designing a dynamic pricing model according to the time of use: ToU tariff in two periods. To this end, we considered a market with two retail companies and inter-hour price elasticities taken from the literature. This means that the residential electricity demand for each of the defined periods depends on the price of the period itself and the prices of the rest of the hours. Additionally, we took into account that consumers may decide to switch retailer according to their profile, therefore incorporating switching costs to our model.

Coinciding with international experience, results show that the price signal to consumers is quite effective to modify their consumption pattern, providing demand is sufficiently elastic. The cost for consumers is lower when both inter-hour and retailer price elasticities increase. We observe peak shaving and efficiency improvements for consumers of 18% in winter and 14% in summer. Furthermore, a ToU scheme is always better than a fixed price when demand is elastic. However, owing to the low values of inter-hour elasticity that were considered for the off-peak period, we did not observe a price reduction at those hours. If consumers do not react significantly to a decrease in prices in the hours where the system is underused, the model does not respond by proposing reduced prices for those periods.

Finally, the application of dynamic electricity prices to residential customers is currently very limited, and thus their impact on the future and how they may affect consumers' behavior is yet unknown. In this regard, the presented simulations are a first step and an even more comprehensive analysis about the market conditions and consumers' reaction to inter-hour and retailer prices would need to be performed (even with the addition of field studies). As further research we plan to relax some of the assumptions we made when defining model (e.g. increasing the number of retailers -set to two in the current model-, differentiating companies according to their size -number of customers- or to their willingness to set more favorable prices for certain periods, distributing consumers not uniformly -currently we assume that there are not differences between consumers and all of them face the same price schedule-, increasing the simulations up to 24 periods, etc.) which would bring our model nearer to reality. In any case, the resemblance of our results with the prices applied in other countries, and even with the prices of the regulated tariff already implemented in Spain, provides an idea of the potential of our model, in spite of the aforementioned limitations.

Chapter 6

Conclusions and Further Research

This thesis is a contribution to the energy policy literature. Overall, we analyze the effect of Renewable Energy (RE) production in the Spanish electricity market in the period 2008-2013 from an economic perspective.

Chapter 2 quantifies the economic impact of the electricity produced by RE sources (RES-E) from the consumer's perspective, both at the aggregate level and by type of technology, in order to determine how expensive RE is. Since one of the main findings of this chapter is that the system of Feed-in Tariffs (FIT) and Feed-in Premiums (FIP) was not sustainable from 2010 onwards, Chapter 3 explores the effect of an alternative regulatory scheme based on Tradable Green Certificates (TGC) for Spain. This chapter concludes that, from 2009 onwards, a TGC market with the right setting could have been more cost-efficient than the incentives based on FIT-FIP.

Following two chapters that focus on the incentive structure, Chapter 4 goes a step forward and analyzes the effect of RES-E on other producers. We observe that the entry of RE into the Spanish electricity market led to a strategy change in Combined Cycle bidding strategies. We detect two patterns: first, the market became more competitive during 2009 and 2010; however, Combined Cycle plants started submitting higher price bids in 2011 and thus electricity prices increased from 2011 to 2013. Comparing the results of Chapters 2 and 4 we observe that the merit order effect decreased when Combined Cycle producers became less competitive, and this had the effect of increasing the net cost for consumers.

Finally, Chapter 5 sheds light on another effect of RE, which is the intermittent nature of some of these technologies (e.g. wind or solar) that produces inefficiencies when the electricity system is underused. After designing various tariffs based on Time of Use (ToU) pricing, we find that if demand elasticity is high enough, consumers could react to electricity prices and exhibit a more efficient consumption pattern.

These questions are relevant because the environmental and socio-economic benefits of RES-E have to be compared to their economic costs in order to determine the optimal level of public support that renewable technologies should receive. As a final concluding remark we observe that RES-E induced important market savings in the Spanish electricity market. However, the energy policy design is crucial in order to guarantee the sustainability of the system.

Looking at Chapter 2 in more detail, the focus is the economic assessment of the net costs of RES-E (from the consumer's perspective) by comparing the savings associated to the merit order effect to the costs of the incentive scheme. We develop a market clearing algorithm that provides market outcomes and serves to simulate electricity prices and quantities for different scenarios. We compare the actual situation with high shares of RES-E with a counterfactual scenario without RES-E.

In Chapter 2 we conclude that the combination of FIT and FIP has been a cost-effective instrument to promote renewable electricity in Spain, since it contributed to the taking off of green participation in the pool. This caused a participation increase from 29% in 2008 to 60% in 2013, and led to a 25-45 EUR/MWh price reduction on the day-ahead market, depending on the year. However, our results indicate that green energy pays for itself up to a point and we empirically show that Spain passed that breaking point in 2010. Although net benefits were positive during 2009 and 2010, the decrease in price due to green sources from 2010 on was not able to overtake the increase in the incentives. This rise in regulatory costs was mainly due to the boost of RE production in the pool combined with high FIT and FIP for some technologies. Nevertheless, we observe significant differences when analyzing each renewable source separately and we show that wind and hydro-generation were profitable, whereas solar and biomass were not.

We observed in Chapter 2 that one important question is the design of the incentive mechanism, since not all public support systems are equally effective in providing incentives for investment in RES at the lowest possible cost. Therefore, Chapter 3 is based on the fact that most renewable technologies are currently still not ready to compete on the market without incentives, but at the same time they no longer need the high levels of support received in the past. In Chapter 3 we develop and implement a theoretical model based on a quadratic penalty function, with the aim of analyzing the interaction between the TGC market and the electricity market whith both markets working under perfect competition. Therefore, higher deviations from the target are more heavily penalized than smaller ones.

Our model shows that there is a transmission of market signals which makes the TGC market more efficient when compared to the FIT system. We show that if a TGC system had been implemented in Spain after 2009, the cost of the incentive scheme could have been lower than with the FIT scheme for similar levels of renewable participation. Furthermore, if we consider the minimum requirement for RES-E for 2020 (40% of RES-E) in order to meet the target, the TGC system results in lower costs than the FIT from 2010 onwards. This result is due to the fact that a regulatory system based on TGC reacts to market changes while a FIT incentive scheme does not. In this regard, the role of policy makers is crucial when setting the value for the scale parameter of the penalty function and the quota for green participation on the market.

We also observed in Chapter 2 that the merit order effect was lower in the period 2011-2013. Electricity demand is very sensitive to economic conditions and the strong contraction in the economic activity of the country during that period could have affected the demand of energy and resulted in a lower merit order effect, since electricity price reductions due to RE dropped. However, lower price reductions could also be a consequence of changes in other producers' bidding strategies. The direct effect of RES-E has been largely addressed in the literature (price reduction), but the indirect effects on the strategy of other market participants still remained unexplored. This is precisely what we analyze in Chapter 4.

In Chapter 4 we test the hypothesis that the market became more competitive after the introduction of RES, due to less market concentration after the entry of renewable producers. To carry this out, we explore the evolution of Combined Cycle bidding strategies in the Spanish pool during the period 2002-2013. We construct synthetic supply curves based on the behavior of Combined Cycle producers when RE participation was lower and we observe how electricity prices would have evolved if this synthetic bidding would have taken place.

Our simulations show that Combined Cycle plants certainly evolved after large participation of RES on the electricity market. We identify two different strategies for the period where the RE share was higher (2009-2013). In the accommodating strategy, applied during 2009 and 2010, Combined Cycle units bidded at lower prices in order to guarantee their matching in the spot market. During the period 2010-2013, however, we detect an inhibition strategy and some of the Combined Cycle generators started submitting higher price bids in order to avoid their participation in the spot market. The accommodating strategy seems to be consistent with the hypothesis that firms would react to a less concentrated market with more competitive strategies. On the contrary, the inhibition strategy corresponds to a period where market conditions make the pool less attractive to Combined Cycle producers. Therefore, the participation of RE on the Spanish electricity market not only led to a decrease in equilibrium prices, but it also caused a change in Combined Cycle bidding strategies in the spot market. Combined Cycle units are bidding at higher prices from 2011 and it should be taken into account in the merit order effect analysis of RES.

Chapter 5 deals with the design of electricity prices for final residential consumers. A key element to improving the technical efficiency of an electricity system with high shares of intermittent RE is the design of pricing policies that reflect actual generation costs. In this regard, prices with hourly differentiation serve a dual purpose. On the one hand, they permit managing the costs of the system in a more efficient way, by incorporating differences in prices which are positively correlated with cost variations. On the other hand, this difference in prices encourages customers to change their behavior, which again contributes to improving the efficiency of the system by shifting consumption from hours where generation is more costly to other periods where it is less expensive.

While Chapters 2, 3 and 4 focused on the wholesale electricity market (the supply of electricity), Chapter 5 sheds light on the functioning of the retail market in Spain (the demand of electricity). We design a dynamic pricing model that considers both the effect of inter-hour energy demand and the retail price. Analyzing the reaction of residential consumers with respect to price changes may give the policy makers important information on the potential for regulation of residential energy prices.

If consumers react to other retailers' prices, lower electricity prices could be achieved. To this end, we propose a model based on ToU pricing and add the effect of retailer competition, which would depend on switching costs. We consider a market with two retail companies and two consumption periods: peak and off-peak. For the empirical part, elasticity values for a baseline scenario are taken from the literature. We also simulate alternative pricing schemes for different elasticity values and compare the results.

Coinciding with findings from other countries, results in Chapter 5 show that the price signal to consumers is quite effective in modifying their consumption pattern, providing demand is sufficiently elastic. The cost for consumers is lower when both inter-hour and retailer price elasticity increase. We observe peak shaving and efficiency improvements for consumers of 18% in winter and 14% in summer. Furthermore, a ToU scheme is always better than a fixed price when the demand is elastic. However, owing to the low values of inter-hour elasticity that were considered for the off-peak period, we did not observe a price reduction at those hours. If consumers do not react significantly to a decrease in prices in the hours when the system is underused, the model does not respond by proposing reduced prices for those periods.

In broad strokes, this thesis reports a number of important findings: renewables have served to reduce consumer costs in Spain, although since 2010 the FIT system as a whole has not been successful. From that moment on, a properly designed system based on TGC could have reduced regulatory costs of renewables in Spain. On the other hand, other competitors on the market have also been affected by the massive influx of RE and have modified their strategies. At first, Combined Cycle producers became more competitive, but since 2011 the market has been less competitive, despite being less concentrated. Moreover, some of the drawbacks of the intermittency of some renewable technologies could be avoided with a new pricing scheme that considers the demand elasticity. If consumers react to inter-hour and inter-retailer prices, their consumption pattern could be more efficient.

However, there is still much to be done in the analysis of the effect of RE in Spain. Chapters 2, 3 and 4 only focus on the effect of the presence of RES-E and cogeneration on the day-ahead market, not taking into account the cost of other services (capacity payments, ancillary services, etc.). We observed that the role of secondary markets has been increasing since 2008, so there is a need to include these markets in further research.

More specifically, in Chapter 2 we did not include the economic effect of avoided emissions derived from the use of clean technologies. These savings should also be included in the net effect of RE.

Concerning Chapter 3 we considered a competitive electricity market for our model. However, results from Chapter 4 suggest that some electricity producers could be exercising some degree of market power. Therefore, in the future we propose to run this model with a non-competitive approach and compare the results. Additionally, some of the model assumptions could be relaxed in future versions (e.g. allowing certificates to have a longer lifetime, including different multipliers for some technologies or modeling uncertainty). The model could also be extended to include a multi-country market, due to the fact that a country with "cheap" RES-E, as is the case for Spain, could then sell certificates to another country with more expensive RE.

Emission Trading Systems (ETS) could be another very interesting possibility for further research for Chapter 3. Despite the fact that TGC and FIT are designed to support RES-E production rather than to reduce emissions, both goals are closely related. In fact, an increase in RE may reduce emissions when there is a substitution effect of black energy with green energy. We should therefore analyze both markets (TGC and ETS) individually but also the interactions between them.

For Chapter 4, apart from including secondary markets in the analysis, in order to see if Combined Cycle production has been affected in any of them as a consequence of RE participation, we could also use time series analysis to detect structural changes in bidding strategies. If results under our synthetic bidding approach and time series analysis coincide, the conclusions of our analysis would be more robust.

Finally, Chapter 5 is a first step in the design of dynamic pricing policies for Spain, but it is still necessary to perform an even more comprehensive analysis on the market conditions and consumers' reaction to inter-hour prices and retailer competition (even with the addition of field studies as a last step). The next step of our research is to relax some of the assumptions of our model. We would like to increase the number of retailers, different companies according to their size and increase the simulations up to 24 periods. This would make our model closer to reality.

Appendix A

Code for the market clearing algorithm

We use data associated with the following information: hourly bids and production units. The software used in the analysis is STATA version 11.

First of all, we implement the market algorithm as an `ado-file` to find the amount of energy traded and the market price in equilibrium for a specific hour. Second, we prepare a `do-file` that automatically computes all the hourly prices for a whole year. The matching algorithm (`ado-file`) is called inside the `do-file`. The flowchart of the process is visualized in Figure A.1 and can be divided into three different parts: data reading, price computing and data storing.

Step 1. Input data reading

As a first step, the program reads data from two different databases. On the one hand, the bids and asks notified by the market participants of Spain and Portugal and on the other hand, the identification of production units: Special Regime or Ordinary Regime. Recall that all of the buy or sell offers are made in the same market place (MIBEL), specifying the area concerned: MIBEL (when there is no congestion) or Spain/Portugal separately (when there is congestion).

Step 2. Special Regime recognition

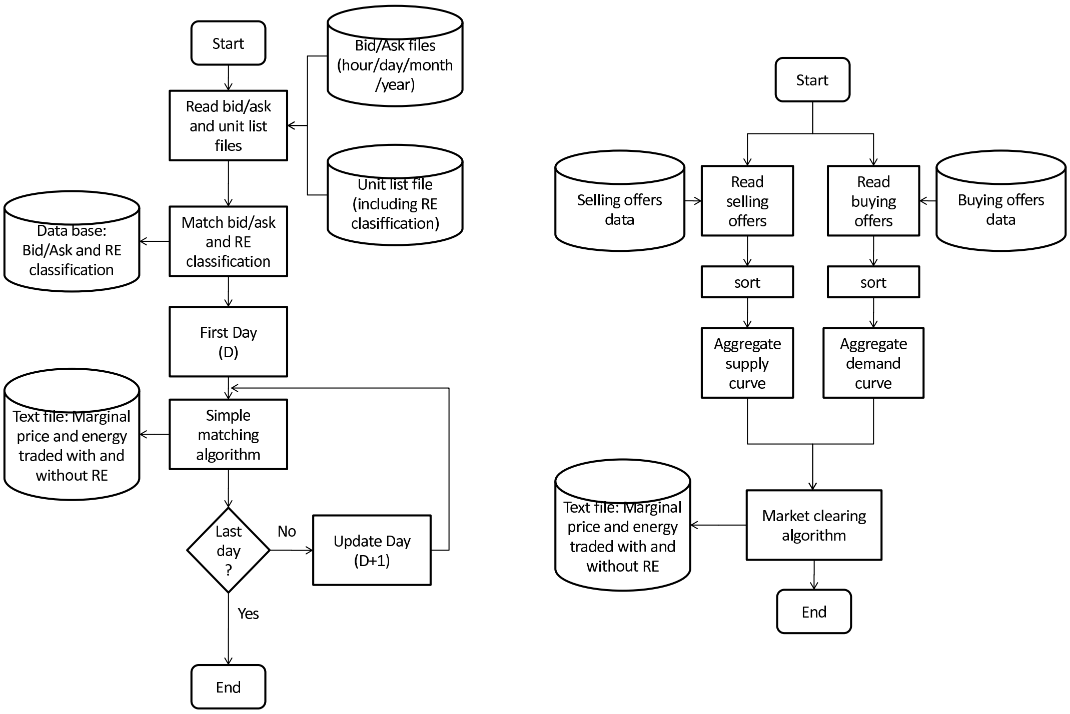
Afterwards, the program labels the entire bid and ask offers, so that Renewable Energy generators are identified by technolgy. This information is stored in a new database and it will be used in the matching algorithm.

Step 3. Simple matching algorithm (iterative)

Subsequently, the program acts as the market operator proceeds and the equilibrium or clearing price calculation starts (see Figure A.1b). The code is divided into three separate algorithms:

FIGURE A.1: Program flowcharts.

(A) Market simulator (`do-file`) (B) Simple matching procedure (`ado-file`)



Source: Own elaboration

Demand curve algorithm

```
capture program drop demand /*use immediate variables: numbers as arguments*/
program define demand

* get variables
args price quantity CV re quantityD

* initialization
version 11
set more off

* create the matrix for bid volume (BV-demand)
mkmat `price' `quantity' `CV' `re', mat(XT) nomissing
mkmat `quantityD', mat(QD) nomissing
clear
local b=rowsof(XT)
mat TVB=J(`b',2,0)
local i=1
sca pi=0
matsum(QD), column(Q)
sca bvmax=float(Q[1,1])
sca bv=0
sca ci=0
while `i'<`b'+1 {
sca pi=float(XT[`i',1])
if XT[`i',3]==0{
sca ci=float(XT[`i',2])
sca bv=bv+ci
}
if XT[`i',3]==1{
sca bv=bv
sca ci=0
}
if `i'==1{
mat TVB[1,2]=bvmax
}
else{
if `i'<`b'-1{
```

```
mat TVB[‘i’+1,2]=bvmax-bv
}
else{
mat TVB[‘i’,2]=bvmax-bv
}
}
mat TVB[‘i’,1]=pi
local i=‘i’+1
}

* add the flat parts of the curve
qui svmat TVB
qui egen BVq=max(TVB2) if TVB2~=., by(TVB1)
mkmat TVB1 BVq if (TVB1~=. & TVB1[_n+1]~=TVB1[_n]), mat(DEMAND)
qui drop BVq TVB1 TVB2
mat H=(0,bvmax)
mat HH=(18.030,0)
mat TRADVB=H\DEMAND\HH

* create the stepwise matrix
local a=rowsof(TRADVB)
local b=‘a’*2
mat TRADVBS=J(‘b’,2,0)
local i=1
local j=1
while ‘i’<‘a’+1 {
if ‘i’==1{
mat TRADVBS[‘j’,1]=TRADVB[‘i’,1]
mat TRADVBS[‘j’,2]=TRADVB[‘i’,2]
local j=‘j’+1
}
else{
mat TRADVBS[‘j’,1]=TRADVB[‘i’,1]
mat TRADVBS[‘j’,2]=TRADVB[‘i’-1,2]
local j=‘j’+1
mat TRADVBS[‘j’,1]=TRADVB[‘i’,1]
mat TRADVBS[‘j’,2]=TRADVB[‘i’,2]
local j=‘j’+1
}
```

```
local i=`i'+1
}

* separate the matrix into 2 variables: price and quantity of energy
qui svmat TRADVBS, names(X)

rename X1 p
label var p "price"
rename X2 BV
label var BV "quantity"
qui drop if _n==_N

end
```

Supply curve algorithm

```
capture program drop supply /*use immediate variables: numbers as arguments*/
program define supply

* get variables
args price quantity CV re

* initialization
version 11
set more off

*matrix for ask volume (AV-supply)
mkmat ‘price’ ‘quantity’ ‘CV’ ‘re’, mat(XT) nomissing
clear
local a=rowsof(XT)
mat TVA=J(‘a’,2,0)
local i=1
sca pi=0
sca av=0
sca vi=0
while ‘i’<‘a’+1 {
sca pi=XT[‘i’,1]
mat TVA[‘i’,1]=pi
if XT[‘i’,4]==0{
if XT[‘i’,3]==1{
sca vi=XT[‘i’,2]
sca av=av+vi
}
if XT[‘i’,3]==0{
sca av=av
sca vi=0
}
mat TVA[‘i’,2]=av
}
else{
mat TVA[‘i’,2]=TVA[‘i’-1,2]
}
local i=‘i’+1
```

```
}

* add the flat parts of the curve
qui svmat TVA
qui egen AVq=max(TVA2) if TVA2~=., by(TVA1)
mkmat TVA1 AVq if (TVA1~=. & TVA1[_n+1]~=TVA1[_n]), mat(SUPPLY)
qui drop AVq TVA1 TVA2
mat H=(0,0)
mat HH=(18.030,av)
mat TRADVA=H\SUPPLY\HH

* create the stepwise matrix
local a=rowsof(TRADVA)
local b=`a'*2
mat TRADVAS=J(`b',2,0)
local i=1
local j=1
while `i'<`a'+1 {
if `i'==1{
mat TRADVAS[`j',1]=TRADVA[`i',1]
mat TRADVAS[`j',2]=TRADVA[`i',2]
local j=`j'+1
}
else{
mat TRADVAS[`j',1]=TRADVA[`i',1]
mat TRADVAS[`j',2]=TRADVA[`i'-1,2]
local j=`j'+1
mat TRADVAS[`j',1]=TRADVA[`i',1]
mat TRADVAS[`j',2]=TRADVA[`i',2]
local j=`j'+1
}
local i=`i'+1
}

* separate the matrix into 2 variables: price and quantity of energy
qui svmat TRADVAS, names(X)

rename X1 p
label var p "price"
```

```
rename X2 AV
label var AV "AV"
qui drop if _n==_N

end
```

Market clearing algorithm (equilibrium)

```
capture program drop equilibrium /*use immediate variables: numbers as arguments*/
program define equilibrium

* get variables
args pD0 qD0 pS0 qS0

* initialization
version 11
set more off

*matrix for tradable volume (p, BV, AV, TV)

mkmat `pD0' `qD0', mat(TRADVB) nomissing
mkmat `pS0' `qS0', mat(TRADVA) nomissing
clear

local a=rowsof(TRADVA)
mat TRADV=J(`a',4,0)
local i=1
sca pi=0
sca av=0
sca bv=0
sca tv=0
while `i'<`a'+1 {
sca pi=TRADVA[`i',1]
sca av=TRADVA[`i',2]
sca bv=TRADVB[`i',2]
sca tv=min(av,bv)
mat TRADV[`i',1]=pi
mat TRADV[`i',2]=av
mat TRADV[`i',3]=bv
mat TRADV[`i',4]=tv
local i=`i'+1
}

*separate the matrix into four variables
qui svmat TRADV, names(X)
```

```
rename X1 p
label var p "price"
rename X2 AV
label var AV "Ask Volume"
rename X3 BV
label var BV "Bid Volume"
rename X4 TV
label var TV "Tradable Volume"

* EQUILIBRIUM: marginal system price (pm) and maximum tradable volume(MTV)
qui egen MTV = max(TV)
qui gen systemquantity=MTV if TV==MTV
qui gen systemp=p if TV==MTV
qui egen MSP=min(systemp)
qui gen systemprice=MSP if systemp==MSP
qui drop systemp MTV MSP

end
```

Appendix B

Notation

Table B.1: Notation of the model.

Generating sector	
h	period of clearing on the electricity market: one hour ($h = 1, 2, \ldots, 8760$ or 8784)
H	period of clearing on the certificates market: one year measured in hours ($H = 8760$ or 8784)
N	number of firms on the generation market
c_{b_h}	intercept of the hourly marginal cost function of black electricity
c_{g_h}	intercept of the hourly marginal cost function of green electricity
c_h	parameter related to the quadratic term of the hourly cost function of each individual generator ($c_h > 0$)
q_{b_h}	quantity of black electricity (non-renewable) sold by one generator in one hour
q_{g_h}	quantity of green electricity (renewable) sold by one generator in one hour
q_{G_h}	total quantity of electricity (non-renewable+renewable) sold by one generator in one hour ($q_{G_h} = q_{b_h} + q_{g_h}$)
Q_{b_h}	aggregate supply of black electricity in one hour
Q_{g_h}	aggregate supply of green electricity in one hour
Q_{G_h}	aggregate supply of electricity in one hour($Q_{G_h} = Q_{b_h} + Q_{g_h}$)
Q_b	annual aggregate supply of black electricity
Q_g	annual aggregate supply of green electricity
Q_G	annual aggregate supply of electricity ($Q_G = Q_b + Q_g$)
x_G	amount of TGC sold by one generator in one year
X_G	annual aggregate supply of TGC
Retailing sector	
K	number of retailers
a_h	parameter of the hourly demand function for electricity
b_h	parameter of the demand function for electricity
q_R	total quantity of electricity bought by one retailer in one year
Q_{R_h}	hourly aggregate demand for electricity
Q_R	annual aggregate demand for electricity
x_R	amount of TGC bought by one retailer in one year
X_R	annual aggregate demand for certificates
Market prices	
p_{e_h}	hourly price of electricity at the pool
p_c	annual price of the certificates at the TGC market
p_{FIT}	annual price of the FIT system
Policy variables (regulated)	
α	quota of green electricity imposed by the policy maker ($0 \leq \alpha \leq 1$)
f	parameter of the penalty function of one retailer ($f > 0$)
F	parameter of the aggregate penalty function ($F > 0$)
s	price to the end-users of electricity
x	retailers' obligation to purchase TGC ($x = \alpha q_R$)

Appendix C

Additional results for the TGC model

Table C.1: Model results with calibration for 2008.

year	α	Q_g %	$\hat{Q}_g$ %	Q_g TWh	$\hat{Q}_g$ TWh	Q TWh	$\hat{Q}$ TWh	p_e EUR/MWh	$\hat{p_e}$ EUR/MWh	p_{FIT} EUR/MWh	$\hat{p_c}$ EUR/MWh
2008	0.31476	28.3	28.4	65.52	64.94	231.48	228.57	64.43	61.55	49.01	49.01
2009	0.31476	39.7	30.4	81.92	62.78	206.42	206.29	36.96	50.25	75.46	19.55
2010	0.31476	47.9	34.6	94.01	66.95	196.35	193.28	37.01	57.76	78.13	0
2011	0.31476	51.6	36.5	95.48	65.00	185.10	177.85	49.93	75.80	74.89	0
2012	0.31476	55.1	38.9	102.28	67.66	185.77	174.05	47.23	73.62	83.12	0
2013	0.31476	58.9	43.5	109.82	77.83	186.59	178.94	44.26	75.55	82.04	0

Source: Own elaboration based on data from OMIE and CNMC.

Table C.2: Model results with calibration for 2010.

year	α	Q_g %	$\hat{Q}_g$ %	Q_g TWh	$\hat{Q}_g$ TWh	Q TWh	$\hat{Q}$ TWh	p_e EUR/MWh	$\hat{p_e}$ EUR/MWh	p_{FIT} EUR/MWh	$\hat{p_c}$ EUR/MWh
2008	0.53092	28.3	40.8	65.52	95.85	231.48	235.02	64.43	36.84	49.01	202.46
2009	0.53092	39.7	45.4	81.92	95.66	206.42	210.85	36.96	30.36	75.46	111.98
2010	0.53092	47.9	47.5	94.01	93.19	196.35	196.11	37.01	37.59	78.13	78.13
2011	0.53092	51.6	49	95.48	90.66	185.10	184.96	49.93	55.16	74.89	52.93
2012	0.53092	55.1	50.4	102.28	91.49	185.77	181.41	47.23	54.38	83.12	34.85
2013	0.53092	58.9	52.7	109.82	96.91	186.59	183.92	44.26	57.31	82.04	12.09

Source: Own elaboration based on data from OMIE and CNMC.

Table C.3: Model results with calibration for 2011.

year	α	Q_g %	$\hat{Q}_g$ %	Q_g TWh	$\hat{Q}_g$ TWh	Q TWh	$\hat{Q}$ TWh	p_e EUR/MWh	$\hat{p}_e$ EUR/MWh	p_{FIT} EUR/MWh	$\hat{p}_c$ EUR/MWh
2008	0.57052	28.3	43.1	65.52	101.71	231.48	236.24	64.43	32.22	49.01	231.51
2009	0.57052	39.7	48.1	81.92	102	206.42	212.08	36.96	26.69	75.46	129.38
2010	0.57052	47.9	50	94.01	98.59	196.35	197.33	37.01	34.01	78.13	96.82
2011	0.57052	51.6	51.3	95.48	95.62	185.10	186.35	49.93	51.20	74.89	74.89
2012	0.57052	55.1	52.6	102.28	96.21	185.77	182.93	47.23	50.65	83.12	57.34
2013	0.57052	58.9	54.4	109.82	100.66	186.59	184.93	44.26	53.78	82.04	35.49

Source: Own elaboration based on data from OMIE and CNMC.

Table C.4: Model results with calibration for 2012.

year	α	Q_g %	$\hat{Q}_g$ %	Q_g TWh	$\hat{Q}_g$ TWh	Q TWh	$\hat{Q}$ TWh	p_e EUR/MWh	$\hat{p}_e$ EUR/MWh	p_{FIT} EUR/MWh	$\hat{p}_c$ EUR/MWh
2008	0.61502	28.3	45.6	65.52	108.36	231.48	237.63	64.43	27.03	49.01	264.53
2009	0.61502	39.7	51.1	81.92	109.2	206.42	213.50	36.96	22.56	75.46	149.12
2010	0.61502	47.9	52.6	94.01	104.71	196.35	198.93	37.01	30.01	78.13	118.06
2011	0.61502	51.6	53.9	95.48	101.28	185.10	187.94	49.93	46.73	74.89	99.97
2012	0.61502	55.1	55.1	102.28	101.75	185.77	184.81	47.23	46.39	83.12	83.12
2013	0.61502	58.9	56.4	109.82	104.99	186.59	186.13	44.26	49.73	82.04	62.31

Source: Own elaboration based on data from OMIE and CNMC.

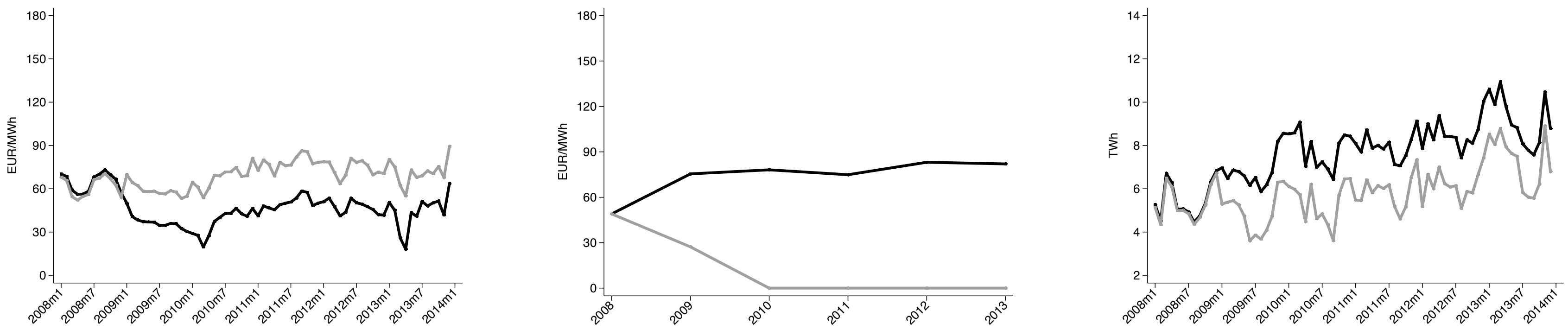
Table C.5: Model results with calibration for 2013.

year	α	Q_g %	$\hat{Q}_g$ %	Q_g TWh	$\hat{Q}_g$ TWh	Q TWh	$\hat{Q}$ TWh	p_e EUR/MWh	$\hat{p}_e$ EUR/MWh	p_{FIT} EUR/MWh	$\hat{p}_c$ EUR/MWh
2008	0.64717	28.3	47.4	65.52	113.21	231.48	238.64	64.43	23.33	49.01	288.62
2009	0.64717	39.7	53.3	81.92	114.44	206.42	214.55	36.96	19.59	75.46	163.50
2010	0.64717	47.9	54.6	94.01	109.18	196.35	200.12	37.01	27.15	78.13	133.56
2011	0.64717	51.6	55.7	95.48	105.44	185.10	189.13	49.93	43.46	74.89	118.37
2012	0.64717	55.1	56.8	102.28	105.89	185.77	186.38	47.23	43.33	83.12	102.09
2013	0.64717	58.9	57.9	109.82	108.27	186.59	187.1	44.26	46.78	82.04	82.04

Source: Own elaboration based on data from OMIE and CNMC.

Figure C.1: Market data (black) vs. Model results (gray) with period parameters from 2008.

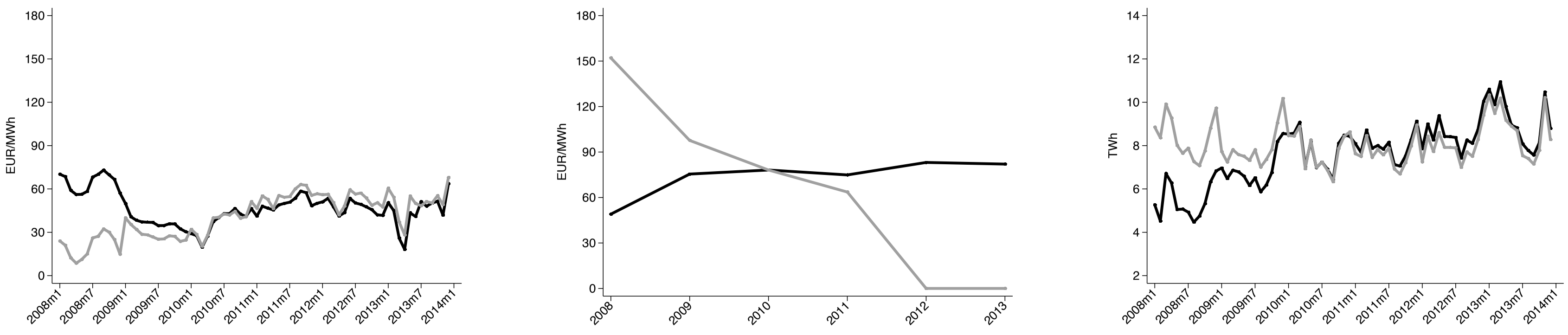
(a) Electricity Price (b) Certificate Price (c) Green Electricity



Source: Own elaboration based on data from OMIE and CNMC.

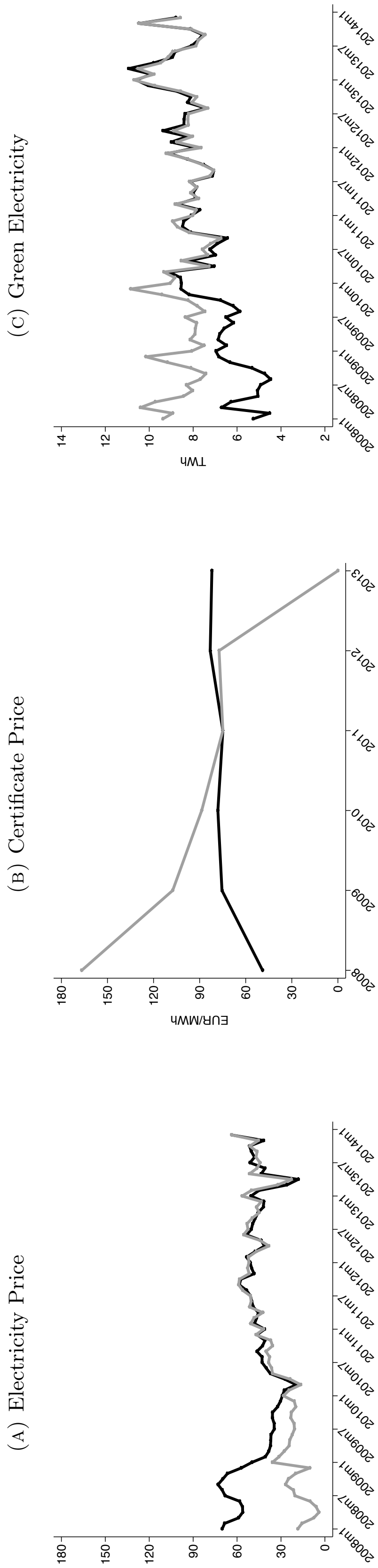
Figure C.2: Market data (black) vs. Model results (gray) with period parameters from 2010.

(A) Electricity Price (B) Certificate Price (C) Green Electricity



Source: Own elaboration based on data from OMIE and CNMC.

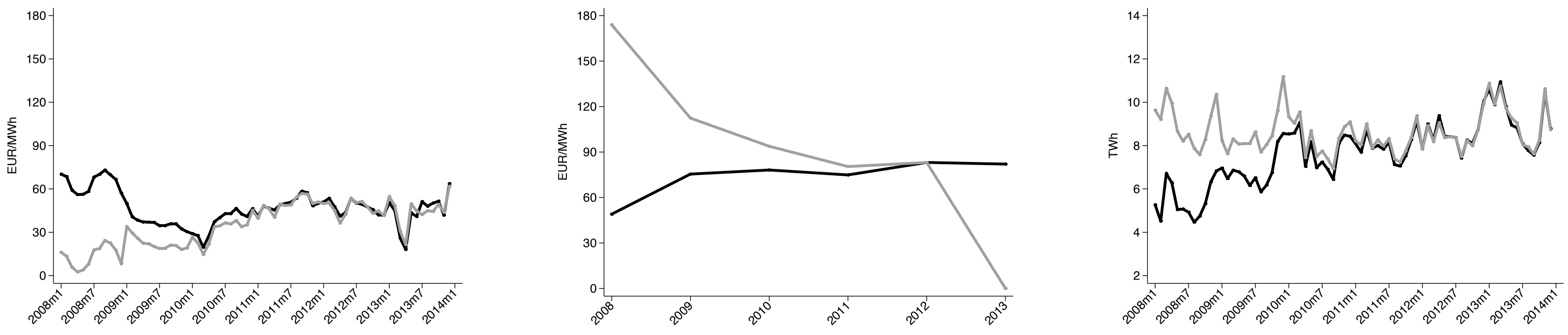
Figure C.3: Market data (black) vs. Model results (gray) with period parameters from 2011.



Source: Own elaboration based on data from OMIE and CNMC.

Figure C.4: Market data (black) vs. Model results (gray) with period parameters from 2012.

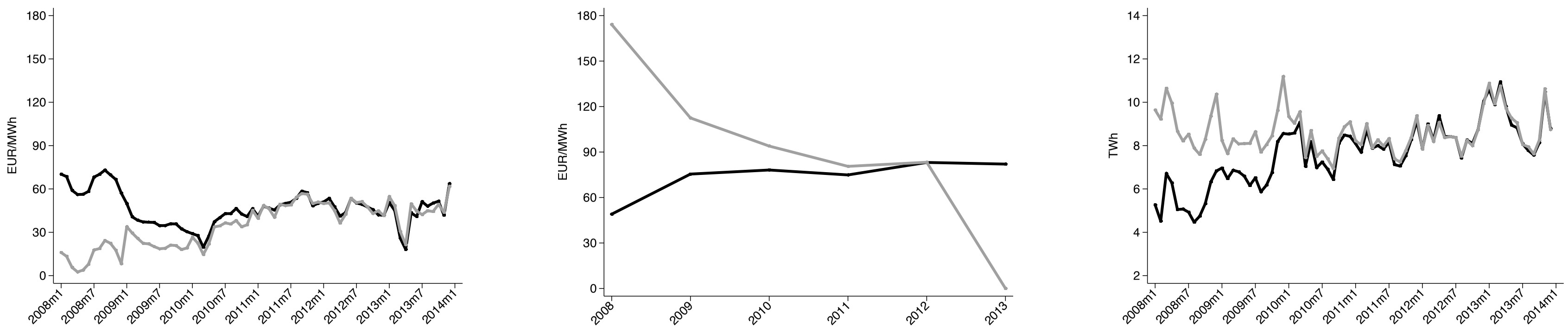
(A) Electricity Price (B) Certificate Price (C) Green Electricity



Source: Own elaboration based on data from OMIE and CNMC.

Figure C.5: Market data (black) vs. Model results (gray) with period parameters from 2013.

(a) Electricity Price (b) Certificate Price (c) Green Electricity



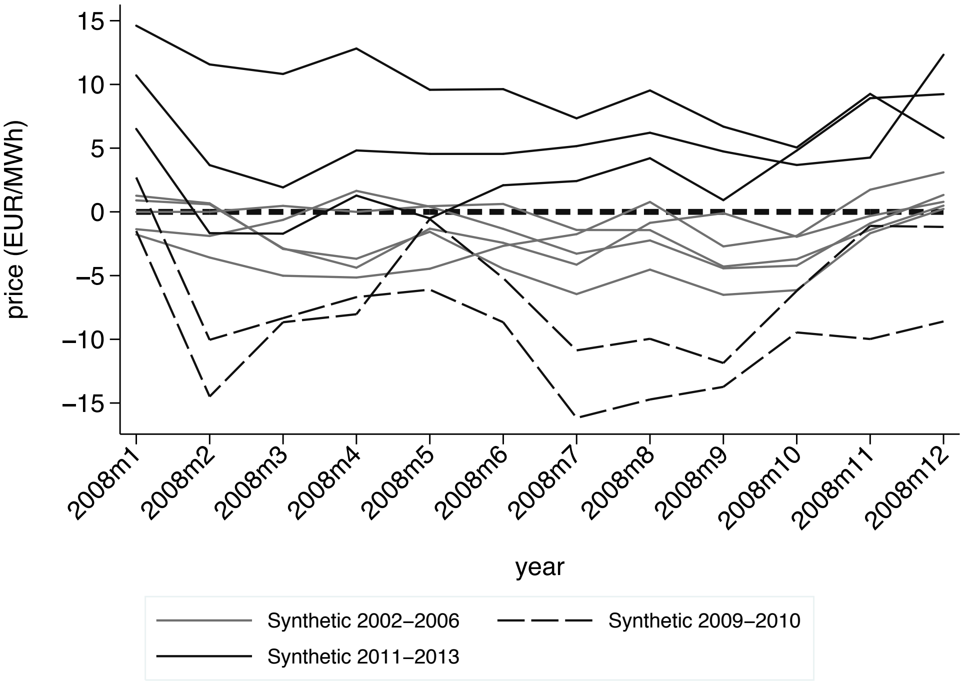
Source: Own elaboration based on data from OMIE and CNMC.

Appendix D

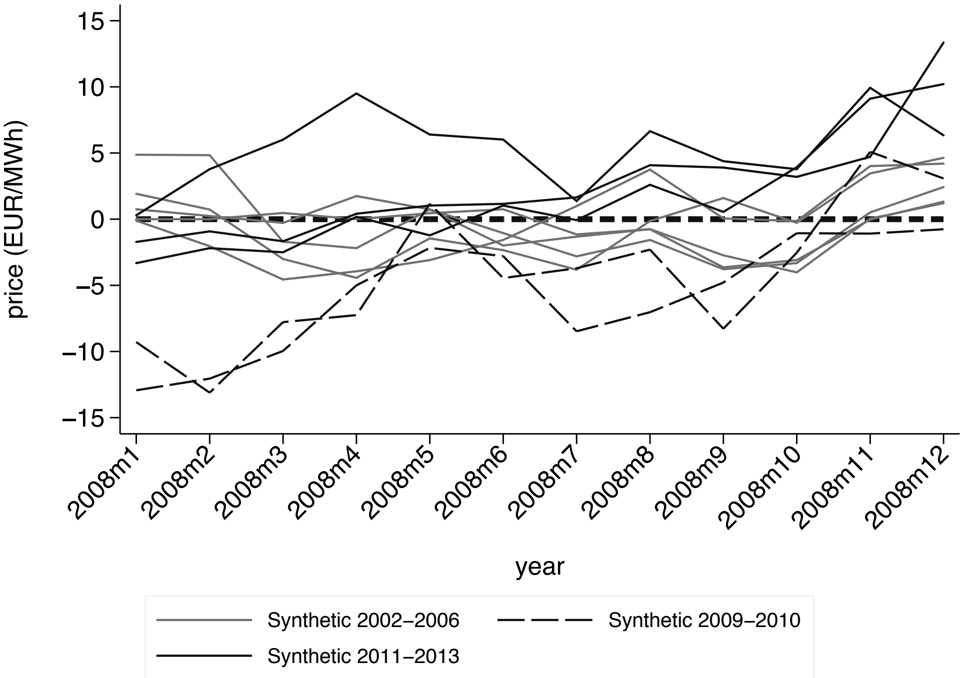
Actual and synthetic electricity price series: Static Synthetic Scenario

FIGURE D.1: Price differences (synthetic - actual) [EUR/MWh] with reference year 2002-2006 and 2009-2013. Year 2008.

(A) Original bids



(B) Change in gas price



Note: Static Synthetic Scenario.
Source: Own simulations, hourly data from OMIE (2015b) (bids), REE (2002) - REE (2013) (technology identification) and CNMC (2015b) (monthly gas prices).

Appendix E

Descriptive Statistics: Static Synthetic Scenario

Table E.1: Descriptive Statistics for the actual and synthetic prices.

		Mean		Median		Standard Deviation		Skewness		Kurtosis	
		Synthetic (original)	Synthetic (gas price)	Synthetic (original)	Synthetic (gas price)	Synthetic (original)	Synthetic (gas price)	Synthetic (original)	Synthetic (gas price)	Synthetic (original)	Synthetic (gas price)
	2002	39.82	40.21	42.43	43.19	19.38	19.29	-0.20	-0.23	2.19	2.24
	2003	39.36	40.23	42.00	43.00	18.45	18.99	-0.24	-0.19	2.10	2.20
ex-ante	2004	38.82	40.59	41.03	44.72	18.93	19.63	-0.23	-0.27	2.07	2.14
	2005	37.62	40.33	40.00	44.04	20.09	21.66	-0.22	-0.20	2.18	2.28
	2006	39.18	40.24	40.00	41.80	20.23	20.51	-0.09	-0.12	2.12	2.14
actual	2008	40.67		44.72		19.55		-0.27		2.21	
	2009	31.72	35.09	30.66	36.70	18.81	17.13	1.29	-0.29	8.89	2.28
	2010	34.34	36.79	35.01	38.80	19.01	18.07	0.93	-0.27	7.37	2.17
ex-post	2011	44.18	42.63	47.99	46.70	19.79	18.38	0.04	-0.48	4.53	2.65
	2012	50.46	46.53	53.81	50.51	20.75	18.43	-0.38	-0.77	3.69	3.02
	2013	46.59	43.51	49.41	47.60	20.12	18.89	-0.16	-0.42	3.61	2.43

Note: Static Synthetic Scenario.
Source: Own simulations, hourly data from OMIE (2015b) (bids), REE (2002) - REE (2013) (technology identification) and CNMC (2015b) (monthly gas prices).

Appendix F

Pricing policies

Time of Use (ToU) pricing

There are two and four seasonal periods (peak, partial peak, off-peak, and weekend tariff) in these price schemes, according to the average consumption of each time span, known beforehand. Prices are set in a way that a consumption shift from peak hours to off-peak hours is produced, since the price of electricity in hours of high demand is set higher than in periods of reduced consumption.

Critical Peak Pricing (CPP)

This scheme proposes annual prices which are lower for off-peak hours in contrast to substantially higher prices for certain periods which are defined as critical (extremely hot or cold days). The maximal number of critical periods is agreed beforehand with the consumer. However, the critical periods of demand cannot be foreseen with accuracy, since they depend on atmospheric conditions, which limit the efficacy of this pricing system.

Critical Peak Rebate (CPR)

Consumers under this system are compensated for any reduction in consumption with respect to what the retailer expects for certain given critical annual hours (in general, exceptionally hot afternoons in summer or extremely cold nights in winter). This system again strongly depends on weather forecasts, which reduces its efficacy.

Inclining Block Rates (IBR)

This system is the least widespread and it is generally used in combination with other schemes, mainly ToU or CPP. This pricing policy offers rising rates by blocks and the price rises as the customer moves to a higher consumption block.

Real-Time Pricing (RTP)

In this case, the consumer pays a different price for each of the 24 hourly periods of the day. The prices to final customers are thereby subject to the hourly costs of the wholesale market. With the adequate measurement equipments (smart meters), this kind of pricing may even adapt to time periods of less than an hour (half an hour, or even minutes) according to the design of the electricity market they are applied to. With the purpose of avoiding excessive billing during certain peak-hours, consumers could be informed when the price exceeds a given threshold.

Appendix G

International experience of pricing policies

In **Germany** (Hierzinger et al., 2013), the *EnerBest Strom Smart* tariff, implemented in July 2008 by Stadtwerke Bielefeld, is a variable tariff combined with an smart meter, aimed at residential consumers and small businesses. The tariff uses four pricing categories, three for peak hours and one for off-peak hours, applied to different days of the week and different day periods. Whereas from Monday to Friday the tariff is divided into six differentiated pricing periods (but only four different prices), during the weekend there are only two differentiated pricing rates. First, the Off-peak tariff (0.17 EUR/MWh) covers both weekdays and weekends from 00h to 6:15h and from 22:15h to 00h. Second, the tariff Peak 1 (0.2836 EUR/MWh) applies on weekdays from 6:15h to 11:30h and from 17:00h to 19:00h. Third, the tariff Peak 2 (0.2836 EUR/MWh) applies on weekdays from 11:30h to 12:30h. Finally, the tariff Peak 3 (0.2181 EUR/MWh) is used on weekdays from 12:30h to 17:00h and from 19:00h to 22:15h and on weekends from 6:15h to 22:15h.

In **France** (Hierzinger et al., 2013), EDF implemented in 1994 the so-called *Tempo* tariff directed to residential consumers as well as to commercial customers and small industries, in order to reduce the load curve during peak hours, especially in winter, and to reduce the global consumption of electricity. The *Tempo* tariff combines two pricing structures: ToU and CPP, in a same tariff, resulting in a total of six pricing time spans.

The ToU part of the tariff divides each day into three periods: a peak time span, between 6:00h and 22:00h, and two off-peak time spans, one between 22:00h and 00:00h, and another between 00:00h and 6:00h. However, the final price in EUR/kWh is linked to the CPP component of the tariff. Thus, each day is associated to a color, which implies a different tariff. “Red” days are the most expensive and the least frequent. Only working days may be included in this category (never Saturdays, Sundays nor holidays) and a maximum of 22 such days may be included during the whole year, in all cases from November to March. The "white" days are somewhat cheaper and more frequent. There are 43 white days per year, mainly between October and May. Finally, "blue" days are the cheapest and most frequent, being around 300 per year (including all Sundays).

In order to qualify for this tariff, smart meters needs to be installed to enable its billing. Additionally, changes in the tariff may be consulted by the customers the day before its implementation through the EDF web page, by email or message, or placing an especial device that may be incorporated on any electric socket. By the year 2008, 350.000 residential consumers and 100.000 small businesses had contracted this tariff, having reduced the consumption of an average household of 1kW in about 15% in "white" days and 45% in "red" days, and the overall costs of electricity in 10%.

Ireland (Darby and McKenna, 2012; Di Cosmo et al., 2012) established a pilot program carried out between 2009 and 2010, which consisted in the implementation of dynamic pricing combined with information to customers and other encouraging elements (like bimonthly billing). The program was applied to 5000 residential customers and 650 businesses in Ireland. Price schedules were divided into three periods: (i) a peak period from Monday to Friday from 17:00h to 19:00h (holidays excluded), (ii) an intermediate period from 8:00h to 17:00h and from 19:00h to 23:00h, which also included weekends and holidays, and (iii) a third nightly period (from 23:00h to 8:00h).

Results show that the use of ToU programs reduced the overall demand of electricity in Ireland by 2.5% and the peak demand by 8.8%. It is worth mentioning that prices for this program were designed in a way that would keep them neutral with respect to the flat tariff in force, meaning that customers who did not modify their behavior would not get any financial penalty for it.

Italy (Torriti, 2012) is gradually implementing ToU pricing since 2010. The first pilot program, known as *bioraria* tariff, was engaged by 4 million final users. Cheaper price schedules of 0.07078 EUR/kWh are applied on weekends at any hour, and on weekdays between 19:00h and 8:00h, whereas for the rest of the periods 0.09982 EUR/kWh are charged.

In contrast with the experience of France with the *Tempo* tariff, electricity consumption increased by 13.7% as a result of the *bioraria* tariff, despite bills being reduced by 2.2% with respect to flat rates. This apparent contradiction between the effect of prices in France and in Italy may be explained by the dynamic impact of dual prices in the marginal price of electricity. In France, the *Tempo* tariff tends to increase prices, whereas in Italy the *bioraria* is mainly adjusted downwards (Torriti and Grünewald, 2014).

Norway (Hierzinger et al., 2013) implemented during the 2005-2008 period a pilot program of fixed price tariff with return option (Fixed price With Return, FWR) for residential consumers.

Trondheim Energy company replaced the traditional flat tariff with a new contract in which the price of electricity in the spot market was combined with a price coverage for a predefined fixed volume of annual electricity. Thus, the FWR contract is drawn from the spot price[86], the contract price and the volume of the contract. Evidence shows that during 2006, consumers engaging the FWR tariff reduced their consumption by 24.5%.

Sweden introduced RTP in October 2012, but there still are scarce data on household behavior under RTP (Vesterberg et al., 2014). Therefore, we highlight one of the previously implemented pilots. The *Elforks* pilot (Lindskoug, 2006) was implemented during the 2003/2004 and 2005/2006 winter seasons. They used CPP with a higher charge for a maximum of 40 hours per year. The consumer was notified the day before of the time and level of peak price via text message or e-mail. This policy intended to encourage customers to transfer their consumption from peak hours in a more precise way than classic rates that only discriminate between two periods (day and night). The tariff showed a great difference in the price of the maximum peak hour and off-peak times, increasing the incentive to customers to shift consumption. As a result of this pilot, the load was cut back to an average of at least 50% during high price instances.

Concerning pilot programs in the **United Kingdom** (Breukers and R.M., 2013), we highlight the *Energy Demand Research Project (EDRP)*, which was a large project to test consumer responses to different forms of information (advice, historic and real-time feedback, and incentives to reduce overall consumption), combined with ToU pricing and smart meters. The program was conducted from 2007 to 2010 by four energy suppliers and showed effects up to 10% of load shifting from peak to off-peak periods (the effects were higher for weekends than for weekdays).

Outside Europe, Faruqui et al. (2010) review twelve pilot programs of dynamic pricing policies applied in the **United States** and **Canada**. It is concluded that the availability of information about the use of electricity reduces consumption by between 3% and 14%, with a 7% on average. Additionally, it is also shown that the impact of dynamic pricing increases in the presence of measurement devices installed in the households.

In a similar way, Faruqui and Sergici (2010) analyze the experiences on dynamic pricing in different states of the United States. It demonstrates that ToU policies reduce the peak demand by between 3% and 6%, whereas those of CPP make it to decrease by 13% to 20%. Besides, the use of consumption control devices in the households may attain a reduction of peak demand of between 27% and 44%.

Allcott (2011) evaluates the first RTP program for residential consumers in the United States, the *Energy-Smart Pricing Plan*, which has operated in Chicago since 2003. Consumers responded by reducing energy by 5%-14% during peak hours, but they did not increase their demand during off-peak hours. Therefore, this author claims that "RTP should perhaps be

[86] It comprises the spot market price plus the retailer margin.

thought of as a peak energy conservation program, instead of a mechanism to shift consumption from peak to off-peak."

Finally, in 2015 Iberdrola introduced new ToU price schemes in **Spain** (weekend tariff, summer tariff, winter tariff, 8-hour tariff, night tariff ...) which offer electricity consumers the possibility to select different prices according to their consumption pattern. However it is still too soon to analyze the effect of these new programs on electricity demand.

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