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Measuring the Impact of Wind Power and Intermittency

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Abstract

Wind power is crucial to decarbonizing electricity markets but is intermittent, which complicates operational management. The researchers assess the welfare impact of wind power on the Spanish electricity market during the years 2009-2018. They estimate modest adverse effects of wind intermittency on operational costs, even at relatively high levels of wind generation. They examine a policy change that shifted output-based wind subsidies to capacity-based subsidies. The authors find that capacity-based subsidies improved market operations, leading to a reduction in the costs of intermittency. This finding suggests that improved incentive design can diminish the negative impacts of wind intermittency.

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1 Introduction

Following the advice of climate scientists, governments around the world are utilizing a variety of policies to accelerate the shift to renewable energy sources. Although the deployment of renewables is essential to combat climate change, their intermittent nature requires additional services such as balancing and reserves to reliably operate the grid. There is a concern that, as the use of intermittent renewables rises, so too will these operational costs incurred by electricity producers. Operational costs affect the social value of wind and should be accounted for when designing the optimal generation mix (Joskow, 2011a; Borenstein, 2012; Hirth, 2015; Gowrisankaran et al., 2016; Joskow, 2019).

Using high-frequency data from the Spanish electricity market from 2009 - 2018, we quantify the average and marginal impact of wind power on several key components of welfare. Spain passed numerous policies in the past fifteen years to incentivize the rapid installation of wind farms, allowing wind's average hourly generation to satisfy over 20% of electricity demand as of today. The detailed available data, as well as the widespread integration of wind, makes the Spanish electricity market a unique opportunity to evaluate the impact of wind at high generation levels. Furthermore, Spain exists in relative isolation, in conjunction with Portugal, from the rest of the European electricity market. Therefore, in the upper tail of wind generation, when wind can satisfy up to 70% of electricity demand, the Spanish electricity market has limited ability to export, making intermittency a potentially larger challenge. Finally, Spain has experienced defined and well-documented shifts in incentives for wind producers, thus allowing us to explore policy impacts.

We exploit the exogenous variation in hourly wind forecasts to estimate the impact of wind on intermittency costs, prices, and emissions. We consider both linear and semi-parametric specifications to model the impact of wind and confirm that our results are robust to the use of different control variables and time fixed-effects. Our baseline estimates show that raising wind levels by 1 GWh increases operational costs by about 0.19 EUR/MWh, diminishing wind producer profits and consumers' benefits compared to an empirical approach that ignores the intermittency costs. However, we find that the increase in operational costs is not exponentially growing at the level of wind.

We explore to what extent the effect of wind on these costs has changed over time and the extent to which such changes can be associated with explicit market design rules. In particular, we exploit a regulatory change in June 2014 that transitioned wind subsidies from marginal subsidies, which were added to the wholesale price of electricity or implemented as a feed-in tariff, to a payment for installed capacity, subject to availability requirements. This regulatory change potentially reduced the incentives for wind producers to generate during high-wind conditions in which prices are very low, leading to lower emissions reductions per MW of installed capacity. However, it also avoided inefficient dispatch in days of high wind supply. We find that the policy change reduced congestion and adjustment costs by avoiding overbidding at zero prices without reducing wind output.

Given the multi-faceted effects of wind, we quantify its average impact across our ten-year panel on several key welfare aspects. We find that for consumer surplus, the decreasing price of wind outweighs the negative cost associated with paying for subsidies. Non-wind (traditional) producer surplus is lowered by the reduction in prices, while the combined positive effect of subsidies and low marginal cost outweighs the price effect for wind producer surplus.

To account for the full cost of the wind power expansion, we consider a range of values for the investment costs of wind farms as well as the environmental benefits from the emissions reductions derived from increased wind production. We find that if investment costs are 50 EUR/MWh, the value of emissions reductions which leads to positive welfare is around 30 EUR/tCO2. If instead investment costs are 80 EUR/MWh, the threshold value is approximately 130 EUR/tCO_2. Given the high need for decarbonization and recent updates in the social cost of carbon (Newell, Pizer, and Prest, Newell et al.; Bueb et al., 2019), we conclude that wind production improved overall welfare for plausible values of wind investment costs and the social cost of carbon. While subsidising wind was considered to be costly due to early adoption of renewables, which made it more expensive, the increasing marginal damages of climate change make wind subsidies welfare improving even for early adoption.

We highlight two important takeaways. First, wind generation during this period contributed positively to welfare, benefiting consumers, wind producers, and climate goals under reasonable parameters. Second, market design can serve to actively alleviate some of the concerns regarding wind intermittency. We find that a substantive change in market design, moving to capacity-based subsidies from output-based subsidies, reduced the operational costs of accommodating high levels of wind into the grid.

Related literature As our paper evaluates the impact of wind and wind intermittency on multiple components of welfare, we reviewed several strands of literature examining wind's impact on different market outcomes. First, we reviewed the economics literature related to emissions offsets due to wind. Cullen (2013), Novan (2015), Kaffine et al. (2013), Callaway et al. (2015), Siler-Evans et al. (2012) and Sexton et al. (2021) focus on the United States, and examine substitution patterns between renewable sources and traditional producers. They conclude that pollution savings, and their relative value to renewable subsidies, depend on the region, the time of day, and the generational mix. Kaffine and McBee (2018), Gutierrez-Martin et al. (2013), and Dorsey-Palmateer (2019) examine how fossil fuel cycling and inconsistent ramping up and down of power impacts emissions offsets. The first two sources find that intermittency can cause a reduction in emissions savings, whereas Dorsey-Palmateer (2019) concludes that shifts in the generational mix caused by intermittency increase emissions savings.

Next, we examined the literature investigating the impact of wind on market prices. Both Bushnell and Novan (2018) (California) and Gelabert et al. (2011) (Spain) find that overall, renewables decrease electricity prices. However, Bushnell and Novan (2018) determines that at shoulder hours, solar power's overall impact on prices is positive, due to the ramping up and down of traditional electricity sources, which they link to operational costs of ramping. Gelabert et al. (2011) finds consistent negative impacts of wind on prices, but notes that the effect varies from year to year, and was on a diminishing trend. There is ample literature investigating the cannibalization of wind on its own market value due to the reduction in electricity prices as wind penetration increases (Pena et al. (2022), Woo et al. (2011), Mwampashi et al. (2021), Maciejowska (2020), Prol et al. (2020), Hirth (2013), Ketterer (2014)). Eising et al. (2020) specifically noted that this cannibalization is worse for onshore compared to offshore wind, because offshore wind is less volatile. Similarly, Hirth (2016) found that the inclusion of hydroelectricity to smooth the intermittency of wind contributed to more moderate decreases in electricity prices

Third, we summarize the literature investigating the impact of wind on operational costs. Gross and Heptonstall (2008), Swider and Weber (2007), Hirth et al. (2015), Milligan et al. (2011), and Joskow (2011b) develop a baseline for understanding the topic via modeling, literature reviews, and brisk calculations. Gowrisankaran et al. (2016) and Batalla-Bejerano and Trujillo-Baute (2016) conduct research more relevant to this paper on the impacts of renewable intermittency on operational costs. Batalla-Bejerano and Trujillo-Baute (2016) focus their investigation on Spain from 2011 to 2014, and find that intermittency increases operational costs, but the use of flexible generators can partially offset this effect. In the same vein, Ketterer (2014) focuses on the German electricity market, and finds that balancing costs would be reduced if wind forecasts were improved. Hirth (2015) looks at the welfare maximizing penetration level of wind in the European electricity market using EMMA. He finds that the ideal penetration level of wind would be nearly 50% larger, in theory, if the need for balancing and operational costs were removed.

Furthermore, we investigate the literature surrounding the welfare impacts of wind power. Liski and Vehvilinen (2020) look at the welfare impacts in the Nordic market, where there is a relatively larger share of renewables and energy storage opportunities. They find that, due to falling electricity prices, consumer surplus rises sufficiently to cover the cost of subsidies for renewables. Abrell et al. (2019) evaluates the welfare impacts of renewables in Germany and Spain. Specifically for Spanish wind power, they find that the cost of reducing 1 ton of CO_2 through subsidies ranges from 82-258 EUR, which harms producers while benefiting consumers.

Finally, there are two existing papers that evaluate a shift in subsidy payments similar to our policy change of interest. Aldy et al. (2018) uses a natural experiment in the US to compare the performance of wind outcomes in a setting with investment-based vs. output-based subsidies. They find that investment subsidies reduce wind output by 10-20% and are less cost effective than output-based subsidies. Differently, we find that a change in subsidies from output-based to capacity-based neither increases nor decreases curtailment. Instead, we find that capacity-based subsidies are more efficient as they avoid low distorted day-ahead market prices, which lead to added adjustment costs. A similar policy change is also studied by Johnston (2019), with a focus on how the tax treatment of the different subsidy mechanisms affects investment. A key difference between the policy change of their focus and ours is that the subsidy mechanism was specific to each wind farm in the United States case, whereas our policy change affected the existing fleet at a moment in which the expansion of new wind power was no longer driven by a subsidy policy. Therefore, the investment channel is not relevant in our setting. In our case, the distortion of market prices from production-based subsidies dominates. A third paper (Ciarreta et al., 2020) looks at the same policy shift of interest as this paper, but investigates its impact on price volatility, rather than prices and welfare. They find a "structural break" in the Spanish electricity market in March 2014, indicated by a period of increased price volatility, without a significant change in the average value of prices.

The remainder of this paper is structured as follows. In Section 2, we provide a background on the Spanish electricity market structure and its regulations across the sample period. Additionally, we describe the theoretical basis behind our intermittency and welfare analyses, and we describe our data sources with summary statistics. In Section 3, we analyze the relation between wind generation and a variety of market outcomes using a regression approach. In Section 4, we take stock of the evolution of prices, costs, and emissions, to assess the overall welfare changes from wind power. Section 5 concludes.

2 Background and policy context

This section provides background on the main characteristics of wind energy in Spain and on the market design of the Iberian Electricity Market and its renewable policies.

2.1 Market organization

The Iberian Electricity Market is centrally organized in a day-ahead market and up to seven intra-day or real-time markets.[1] In the day-ahead market, producers and consumers submit their supply and demand bids for each of the 24 hours of a delivery day, and production for each hour is auctioned simultaneously using a uniform rule, setting a marginal price of electricity for each hour of the day. The day-ahead plans for roughly all expected daily electricity, whereas sequential markets throughout the day allow for re-trading.

Moreover, the electricity market includes other markets where producers participate adjusting

[1] See Ito and Reguant (2016) for a thorough description of these markets.

production or providing reserves to ensure security and reliability of supply at all times. These additional markets ensure that the grid can be operated in a feasible and reliable manner, e.g., to solve congestion problems or satisfy reliability constraints. Approximately 8.8% of total scheduled energy is traded in these additional markets. These markets can increase the costs of procuring electricity, as final consumers pay for these services in addition to the day-ahead prices. We call these added costs *operational costs*, as they are meant to ensure that the market remains operational.

Several markets contribute to these operational costs, namely, the restrictions market, the frequency market, and the deviations market. The restrictions market takes place first, ie., many hours before the electricity is actually delivered. It takes into account congestion offered into the day-ahead market, which naturally would occur due to the volatility of renewable sources. Second, the frequency market provides reserves or back-up capacity to respond to unexpected deviations in demand or production, due more to uncertainty than volatility. Firms in the frequency market offer their power plants to provide reserve services and get compensated on an individual basis. The last market, which occurs in the last hour before electricity is delivered, is the deviations market. This market solves imbalances between supply and demand in real time, normally due to deviations in demand or renewable generation, rewarding firms that adjust their production on an individual basis to ensure that demand and supply match.

Final consumers pay for most of these costs as a surcharge in their cost per purchased MWh. However, deviation costs due to last-minute wind changes are paid by wind farms if they fail to produce what they had scheduled. If wind farms generate more electricity than scheduled, they get a payment for their surplus energy, but it is a lower price than they would have received if their excess energy had been bid in the day-ahead market. In both cases, shortfall or surplus deviations are effectively penalized when compared to scheduling wind generation more accurately.

In our analysis, we explicitly separate operational costs paid by consumers vs. operational costs paid by wind farms, to appropriately understand the distributional implications of wind intermittency. We define "operational costs" as those paid by consumers as an added marginal fee to the final cost of electricity. These costs are represented in EUR/MWh of demand served. Separately, we consider the deviations costs paid directly by wind farms, which affect their profitability and are not paid by consumers. We represent these wind costs as a cost per MWh of wind produced, as opposed to a cost per unit of demand.

Within the operational costs paid by consumers, we consider three broad categories, as discussed above. First, restrictions costs are the reshuffling costs to ensure that the grid can function, e.g., due to network congestion from renewable generation volatility after the day-ahead and intra-day markets. Plants are compensated to either go up or down in order to satisfy these constraints. Second, frequency services ensure that power plants are readily available in case there is a need. These services include reserves and secondary regulation, among others. These services have been

Table 1: Summary Statistics

	Summary				
	Mean	SD	P25	P50	P75
Actual Demand (GWh)	28.67	4.82	24.54	28.84	32.36
Wind Forecast (GWh)	5.26	2.94	2.95	4.66	7
Solar production (GWh)	.83	1.08	0	.05	1.66
Price DA (EUR/MWh)	45.97	15.78	37.68	47.62	55.69
Operational Costs (EUR/MWh)	3.85	3.12	1.87	3.1	4.92
- Restrictions Costs (EUR/MWh)	2.48	2.34	.99	1.94	3.27
- Frequency Costs (Euro/MWh)	.29	.76	0	.11	.38
- Deviations Costs (EUR/MWh)	1.11	1.36	.42	.74	1.33
Costs to Wind (EUR/MWh of wind)	2.11	2.91	.47	1.31	2.8
CO2 Emissions (tCO2)	7065.07	2728.48	4863	7161.17	9143.79

Notes: Price DA is the price at the day-ahead market. The variable "Operational Cost" is the sum of costs paid by final consumers (restrictions, frequency, and deviations costs). Intermittency costs directly paid by wind producers are captured by "Costs to Wind". Data from 2009 to 2018. $N = 83,840$.

traditionally provided by power plants that are already running or by power plants that are shut down, depending on the type of reserves (and how fast they might be needed). However, during our sample period, regulation changes allowed wind farms to participate in some of these services (see Table A.1). Finally, deviation costs are meant to cover last minute deviations between production and demand. These services are provided by power plants that are already running, who are paid on an individual basis to adjust their output.

Table 1 provides summary statistics for demand, wind production, market prices, and operational costs. We use data from January 2009 to December 2018. The average wind forecasted in that time period was 5.26 GWh (with a median value of 4.66 GWh), or approximately 18.5% (16.4%) of actual demand. In this sample, the average electricity price is around 46 EUR/MWh and average operational costs paid by final consumers are 3.85 EUR/MWh. This represents about 3-10% of the price per MWh (interquartile range), although the relative importance of these costs can fluctuate depending on the conditions of each day. Operational costs to final consumers are the sum of restrictions, frequency, and deviations costs, where restrictions (such as congestion) explain the majority of operational costs. Wind farms also pay costs for their intermittency, when their output deviates from their planned production. These costs are in the order of 2.11 EUR per MWh of wind produced, or about 4% of their profitability on average.

2.2 Regulation

Environmental regulation and government subsidies encouraged investment in renewable energy in Spain during the 2000s. Renewable capacity in Spain experienced a considerable increase since 2005, motivated by feed-in-tariffs and capacity payments. In contrast, aside from combined cycle gas power, most traditional generating technologies maintained fairly constant capacity since 2002. Nowadays, renewable capacity accounts for approximately 25% of all generation in Spain and wind capacity alone accounts for 19% overall.

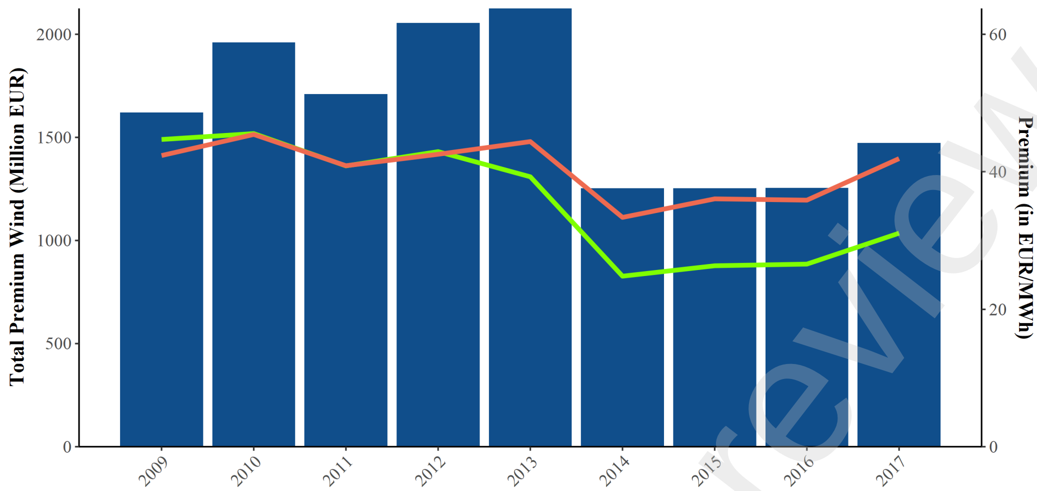
Regulation of renewable power in the Spanish electricity market has changed significantly in the last twenty years. In the beginning, regulation promoted investment in renewable capacity through output-based subsidies. In particular, renewable producers could opt for two pricing schemes since 2007: (a) Feed-in-Premium (FiP), or (b) Feed-in-Tariff (FiT). Under option (a), producers sold their electricity in the electricity market and their price would be determined by the market price plus a premium payment. Under option (b), producers had to offer all their production at a zero price in exchange for a regulated compensation invariable for all scheduling periods. These subsidies encouraged a significant increase in wind production from 5.7% of total electricity generation in 2004 to 18.9% in 2014.[2] This increase in participation pushed wholesale market prices down in the day-ahead market as wind plants offered their energy at zero or near-zero prices. Additionally, wind's intermittent nature required an increasing utilization of adjustment markets where additional, reliable plants guarantee a fast response to changes in electricity generation from wind with respect to forecasts. The cost of these additional services went up as wind participation increased.

To encourage the promotion of wind without creating a consumer backlash, the full cost of subsidising wind was not passed along to consumers. However, Figure 1 shows that the Spanish government substantially increased its total subsidy payments for wind farms in the years leading up to 2013. These subsidy payments, combined with rising operational costs, led to an "electricity debt," in which the regulators of the electricity grid were losing money on wind farms. This debt was unsustainable, leading to a change in subsidy policy.

Subsequent regulation hence focused on eliminating these output-based subsidies and designing a new subsidy scheme to provide an additional economic compensation for renewable energy at lower costs. The Spanish government implemented several regulations between 2012 and 2014 to decrease the "electricity debt." The regulations also promoted the improvement of operational procedures to better integrate wind into the market. Table A.1 in the Appendix presents the most relevant regulations during our sample period. An obvious result of these policy changes can be seen in Figure 1, when the average subsidy for wind farms was reduced from 45 EUR/MWh produced between 2009 and 2013, compared to an average subsidy of 30 EUR/MWh produced between 2014 and 2017.

[2] https://ourworldindata.org/explorers/energy

Figure 1: Total Premium and Subsidies for Wind Energy in Spain



Notes: This figure shows the total premiums paid to wind energy in the Spanish electricity market (in mEUR) and the implied subsidies (in EUR/MWh). The red line shows total subsidy remuneration divided by subsidized wind production while the green line shows total subsidy remuneration divided by all wind production, regardless of its subsidy status. Source: Comisión Nacional de la Energía (2018).

The first regulation in 2012 suppressed the economic incentives for new renewable production facilities, which explains why renewable capacity stopped growing after 2012. The second regulation, in February 2013, eliminated the FiP pricing scheme. Under this regulation all producers under the FiP scheme were moved to the FiT pricing scheme. In July 2013, the government further eliminated the FiT pricing scheme, although the new pricing scheme was not implemented until June 2014. These new regulations affected the arbitrage incentives for wind plants illustrated in (Ito and Reguant, 2016).

In June 2014, the Government implemented a new pricing scheme where renewable producers were compensated by installed capacity rather than produced electricity. This new compensation was based on a capacity payment to compensate investment costs not recovered through the market, and a production payment to provide investment incentives by reducing production costs. Both components were independent of the actual revenues or investment costs of the producers. The new pricing scheme applied to facilities that had not recovered the investment costs previously (mostly capacity installed after 2004). For more than half of the wind farms, the new subsidy worked out such that, when they divided their annual revenues by generation levels, the wind farms would have received an equivalent compensation per MWh of less than 20 EUR/MWh. Therefore, many wind farms decided to opt-out from the scheme and sacrifice the subsidy to receive the market price instead.[3] As a result, a large proportion of wind farms no longer offered their generation

[3] Page 25, https://www.aeeolica.org/uploads/AEE__ANUARIO_2015_web.pdf.

to the market at 0 EUR/MWh, and instead could choose to set their bids higher. In addition, this regulation stated the possibility of renewable sources' participation in adjustment markets, although their participation effectively started only in February 2016.

One important feature of the June 2014 regulatory change is that most wind generation stopped having marginal subsidies proportional to production, and instead were offered subsidies to investment (subject to minimum availability requirements to avoid perverse incentives on maintenance). This change had a very significant impact on the occurrence of zero prices in the day-ahead market, as shown in Figure 2a. It also reduced the incentives for wind farms to offer their output in the market in situations of wind oversupply. However, we do not find evidence of increased curtailment of wind at high-levels of generation, as shown in Figure 2b, something that we econometrically test in the empirical section.

We focus on the change in June 2014 because, empirically, it seems to be the one that had the most substantial impact on the operational costs of integrating wind via the elimination of zero prices. We provide evidence using market data that the policy did appear to impact the operation of the Spanish electricity market via expected channels. However, it is important to keep in mind that other measures undertaken by the regulator as well as market trends can also affect the costs of intermittency. However, this example is still useful to understand the impact of market design on the costs of intermittency.

2.3 Data

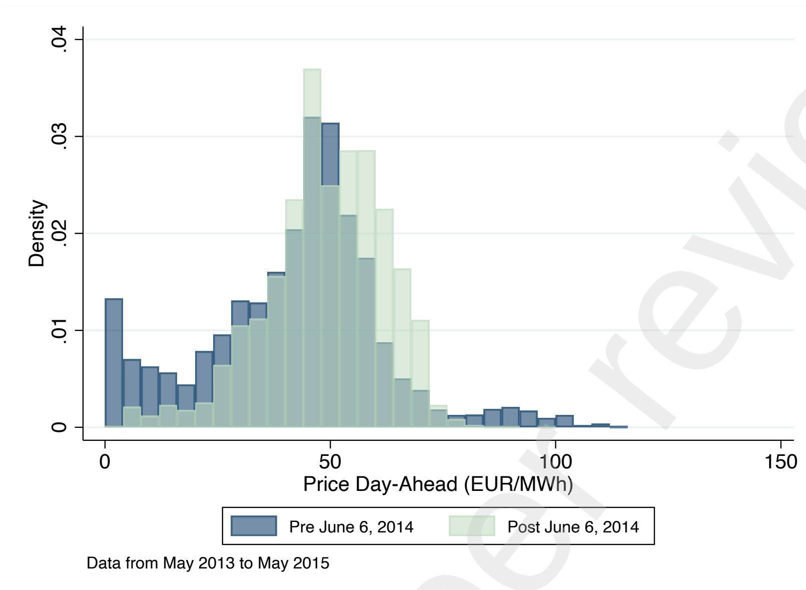
We construct a dataset using publicly available data from the system operator, Red Eléctrica de España (REE), and the the Iberian electricity Market Operator (OMIE). The final dataset includes planning and production outcomes from the system operator at the hourly level. More precisely, it incorporates aggregate demand and supply from each type of generation, market clearing prices, emissions, demand forecasts, and wind forecasts. One of the main advantages of this dataset is that forecasts are observed hourly and for up to 48 hours in advance. This allows us to construct different variables based on these forecasts to compare to actual demand or production delivered. Another advantage is that the data have detailed accounting of operational costs, allowing us to measure the impact of wind on different components of the operation of the grid (restrictions, frequency, and deviations). Moreover, the OMIE datasets include hourly bidding offers at the generator level, allowing us to monitor bidding behaviour over time. Finally, the addition of market prices and emissions expands the scope of this paper to include a full cost-benefit analysis.

We supplement the data from the REE and OMIE with several other sources to account for a variety of additional variables. First, we obtained data on historical natural gas prices from Bloomberg Markets.[4] Prior to March 2010 we utilized the British Virtual Gas Hub Spot Price,

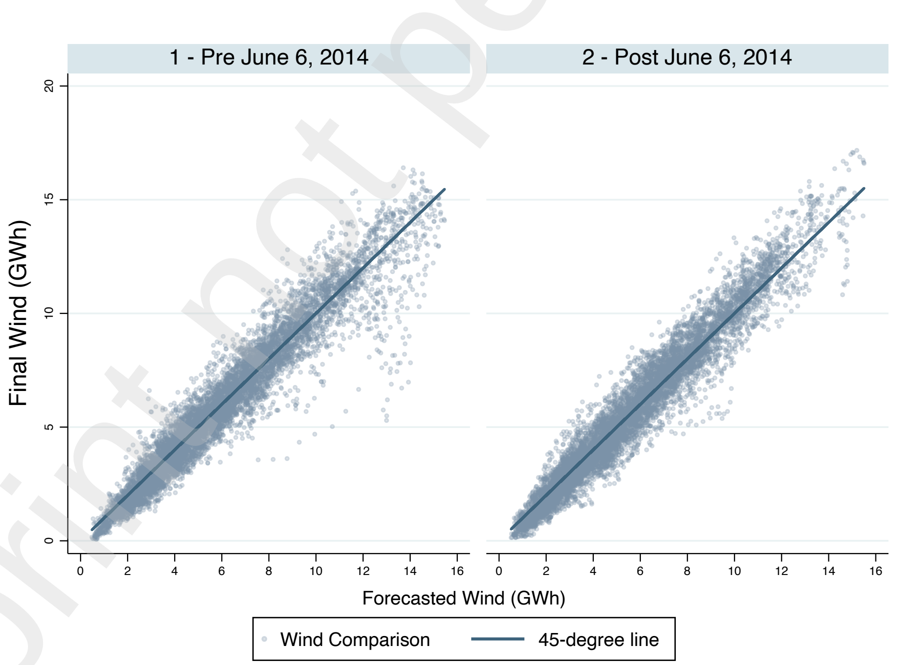
[4] https://www.bloomberg.com/energy

Figure 2: Price and wind outcomes before and after the 2014 policy change

(a) Day-ahead marginal prices before and after policy change



(b) Wind productions vs. wind forecast before and after policy change



Notes: Going from production-based to capacity-based subsidies removes the incentives to bid all wind production at very low prices. The policy change reduced the occurrence of zero prices in the wholesale electricity market, as shown in Panel (a). The policy change did not seem to lead to additional wind curtailment in hours of high wind production, as shown in Panel (b).

after August 2014 we used the Netherlands TTF Spot Price, and in the dates in-between we used an average of the two. Second, we obtained historical weather data on hourly temperature, humidity, pressure, and dew point at a variety of airports across Spain from the Wunderground databases[5] (prior to 2017) and the Tutiempo databases[6] (2017 and 2018). Finally, we downloaded data on daily EU-ETS carbon pricing from the Carbon Price Viewer webpage on the Sandbag Smarter Climate Policy Website.[7]

In addition to detailed market outcomes data, we construct two variables to summarize intermittency: volatility and uncertainty. We define volatility as the changes in delivered wind production between different hours of the day, and across different days. We compute volatility as the standard deviation in delivered wind for rolling intervals of 6, 12, and 24 hours. Figure A.1a shows the distribution of the standard deviation in wind delivered for those different time intervals. One can see that, in the span of 24 hours, it is common for wind to have a standard deviation of around one GWh, and it is not uncommon to have standard deviations above two, which is substantial given average hourly wind production of 5.34 GWh.

We define uncertainty as the difference between forecasted and actual generation. We compute uncertainty as the standard deviation of the differences between forecasted and delivered wind in the periods leading to the time of delivery. We exploit the fact that we observe predicted wind at different intervals: 36 hours in advance, 35 hours in advance, etc. Therefore, we observe how uncertainty in the forecasts is evolving over time and can compute the standard deviation in such forecasts. Figure A.1b shows the distribution of uncertainty when we consider forecasts up to 6, 12, 24 and 36 hours in advance to compute the standard deviation. The measures show that uncertainty is reduced as the time of delivery approaches, but there is still substantial uncertainty left even six hours in advance, with a mode around 150-200 MWh. This implies that the forecast of wind for a given hour can fluctuate in the order of 150 MWh even six hours close to delivery, and some days the forecasts can fluctuate by 500 MWh (approximately 10% of wind generation) or more.

3 Quantifying the impact of wind

We empirically investigate the impact that wind power has had on the operations of the Iberian electricity market. Our goal is to characterize the impacts that wind generation has on several market outcomes, such as prices, operational costs, and carbon dioxide emissions, putting special emphasis on the role of intermittency in explaining the effects. We also explore the temporal evolution of these impacts. We first focus on the impacts on operational costs paid by consumers,

[5] https://www.wunderground.com/history

[6] https://www.tutiempo.net/registros/

[7] https://sandbag.be/index.php/carbon-price-viewer/

such as congestion payments and reliability services, which are very directly linked to intermittency. We then evaluate other market outcomes that are relevant for a comprehensive welfare evaluation (prices, wind revenues, and emissions).

3.1 Operational costs

Our goal is to estimate the fraction of operational costs that are explained by wind production and intermittency. Wind production and intermittency affect restrictions markets causing congestion, increasing the need for back-up capacity in specific nodes of the grid. Changes in forecasts affect firms' positions in intra-day markets, causing over or under production in the grid. Wind production has an impact on frequency markets due to the need for higher reserves to accommodate deviations in production working against deviations in system demand.

We first investigate the average effect of wind generation on all operational costs (in EUR/MWh) using the following specification:[8]

$$Y_t = \beta_0 + \beta_1 W_t + \gamma X_t + \epsilon_t \ , \tag{1}$$

where Y_t refers to the outcome of interest (e.g., total operational costs), W_t is the forecasted wind in the market, X_t includes control variables, and ϵ_t is the error term. In this, as well as future regressions, control variables include daily natural gas prices, as well as hourly forecasted demand, temperature, temperature squared, dew point, and photovoltaic generation. Additionally, we include month-of-sample fixed effects interacted with hourly fixed effects for most specifications. The inclusion of fixed effects is important to control for predictable fluctuations in market conditions (and thus, operational costs) that might not be captured by our controls

We estimate equation (1) using OLS and clustering standard errors at the month of sample level. We exploit the exogenous variation in wind output and intermittency to identify its effects on the outcomes of interest. Therefore, the coefficient of interest is β_1 and represents the marginal effect of a GWh increase in wind on Y_t.

Table 2 presents the baseline results for the impact of wind on total operational costs. We confirm that wind generation tends to increase operational costs. For an additional GWh of forecasted wind generation, our results suggests that operational costs go up by about 0.19 EUR/MWh compared to an average of 3.85 EUR/MWh. This is expected, due to the need for additional balancing services to account for the intermittent nature of wind generation. The results are robust to the inclusion of several relevant controls, such as natural gas prices, which fluctuate substantially during this period, and weather indicators. Intuitively, the price of natural gas also contributes positively to operational costs, due to the role of gas power plants at providing these balancing

[8]The same patterns arise if we focus on costs in thousands of dollars, instead. The measure in EUR/MWh facilitates a direct comparison with market prices, which are in EUR/MWh.

Table 2: Marginal impacts of wind on operational costs

VARIABLES	(1)	(2)	(3)	(4)
Forecasted wind (GWh)	0.194	0.194	0.196	0.191
	(0.0161)	(0.0161)	(0.0159)	(0.0162)
Forecasted demand (GWh)	-0.153	-0.155	-0.157	-0.157
	(0.0188)	(0.0188)	(0.0187)	(0.0188)
Solar production (GWh)	0.0265	0.0323	0.0530	-0.0124
	(0.0691)	(0.0684)	(0.0669)	(0.0645)
NG price (EUR/MWh)		0.0285	0.0243	0.0236
		(0.0424)	(0.0419)	(0.0419)
Mean temperature (F)			-0.0437	-0.0240
			(0.0339)	(0.0358)
Sq. mean temp. (F/1000)			0.256	0.157
			(0.254)	(0.261)
Mean dew point (F)				-0.00933
				(0.00684)
Observations	83,840	83,840	83,840	83,840
R-squared	0.560	0.560	0.561	0.561

Notes: Standard errors clustered at the month of sample. All regressions include fixed effects of month-of-sample interacted with hour.

services, although the effects are noisily measured due to the inclusion of substantial fixed effects. Demand is negatively related to operational costs, due to the fact that the dependent variable is in units of EUR/MWh. While it may be expected that with more energy to be managed the operational costs would increase, instead we believe that economies of scale are having the opposite effect.

Sensitivity to fixed effects Month-of-sample fixed effects account for seasonal variations and wind capacity expansions over time. In Spain, the expansion in wind power mostly preceded our sample of study. That said, we examine the impact of structural changes over time following Bushnell and Novan (2018) by considering a specification without year fixed effects. Additionally, for complete robustness, we evaluate the impact of all combinations of year, month, and hourly fixed effects on our variable of interest, as well as the coefficients attached to solar production and demand forecast.

Table A.2 in the Appendix shows the results of this analysis. In our context, and given the ample variation in wind production, we find that the inclusion of fixed effects does not substantially affect the results. From our central estimate of 0.19 EUR/MWh, we find that including only year fixed effects leads to an estimate of 0.215 EUR/MWh. Removing all fixed effects leads to a larger impact of wind on operational costs, at 0.234 EUR/MWh. Including alternative sets of fixed effects (month-of-sample interacted with day-of-week) leads to similar estimates, all of which range 0.176-0.234 EUR/MWh. Despite the estimates being within a similar range, we use fixed effects to make certain that neither seasonal nor time-of-day outside occurrences in the market (beyond our control variables) bias the results.

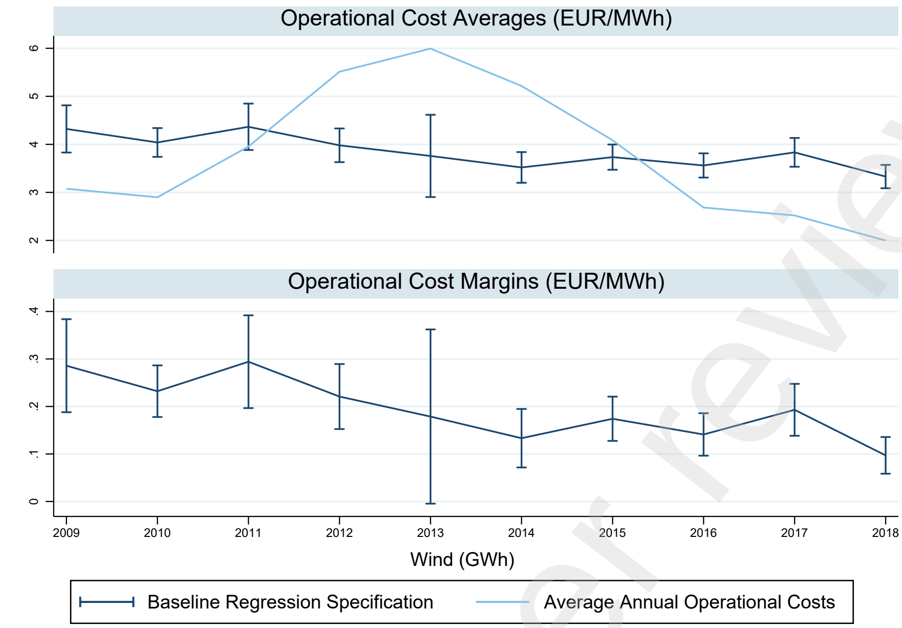
The removal of time fixed effects impacts the effect of solar power on operational costs much more dramatically, as also shown in Table A.2. This is to be expected, as solar power is much more predictable and is highly correlated with hourly seasonality. In the absence of hourly fixed effects, solar is negatively correlated with operational costs due to its zero production in peak evening times. The estimates on forecasted demand are also substantially impacted for the same reason. Wind effects, on the contrary, are robust to fixed effects due the inherent randomness of wind output, which is not true for electricity demand and solar generation.

Annual effects To further examine changes in the impacts of wind over time, we estimate equation (1) with year interaction terms attached to the coefficient of interest. This allows us to explore whether the impacts of wind on operational costs are becoming more or less salient over time for the same level of wind output. Additionally, to simultaneously investigate the impact of the June 2014 policy change, the "year" effect is not defined based on the calendar year, but instead is defined to run from June of one year to May of the next year. For example, the year "2014" is defined to exist from June of 2014 to May of 2015.

Figure 3 depicts the annual marginal and average effects of wind on operational costs via our baseline regression. For reference, the mean annual operational cost is included in the upper panel. The results do not indicate a consistent increasing or decreasing trend in the marginal effect of wind on operational costs over the sample period. Instead, there appears to be a shift starting in 2014, with the marginal impacts being substantially lower. The marginal and average effects dropped from their maximum values in the sample (0.30 EUR/MWh and 4.51 EUR/MWh, respectively) to their minimum values (.06 EUR/MWh and 3.25 EUR/MWh, respectively).

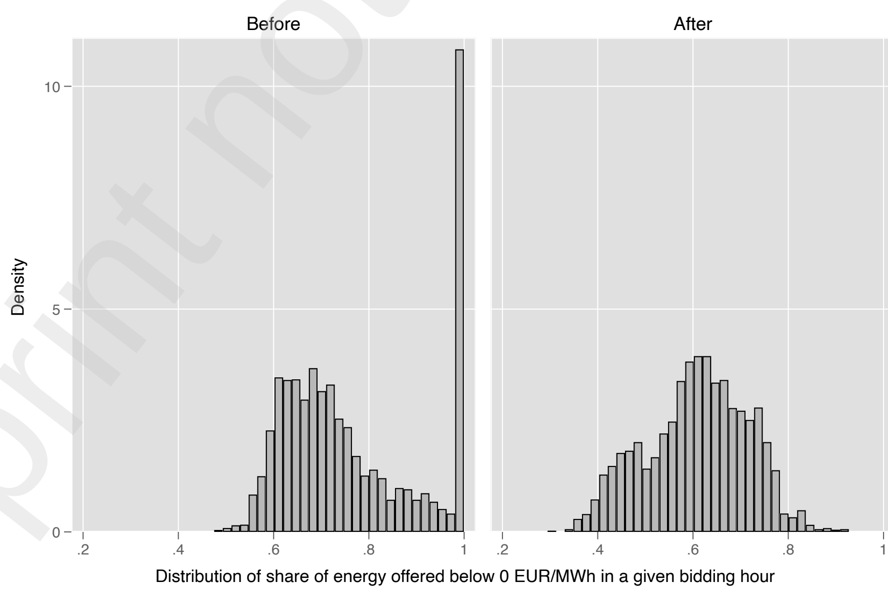
This sharp decline in the marginal cost effect occurs in conjunction with the June 2014 policy change described in Section 2. At the same time period, we also observe a change in bidding patterns by wind farms. We collected hourly bidding data for wind farms in the Spanish electricity market from the Iberian Electricity Market Operator (OMIE) for the year 2014, and determined the percentage of MWh of wind which were offered at 0 EUR/MWh. Figure 4 illustrates the density of these percentages before (Jan-May 2014) and after (June-Dec 2014) the June 2014 regulatory

Figure 3: Annual Average and Marginal Operational Cost Effects



Notes: A look at annual marginal and average effects of wind on operational costs based on equation (1). Mean annual cost variation predicted by wind holding the impact of other variables at their average also included in the upper panel for reference.

Figure 4: Distribution of Wind Levels Bid at 0 EUR/MWh, Before and After June 2014



Notes: Own elaboration based on hourly unit-level bidding data from the Iberian Electricity Market Operator (OMIE) during the year of 2014. We select production units that are linked to wind farm operations before examining the data.

change. Before the policy change, over 10% of hours had instances in which every wind farm offered their production at 0 EUR/MWh. After the policy change, there was not a single instance in which this occurred, showing that wind farms experienced a marked decrease in incentives to bid at low prices. These results are in line with the day-ahead marginal prices observed before and after the policy change in Figure 2a.

We suspect that this change in bidding behaviour sparked by the policy was a main driver of the prominent decrease in operational costs in 2014 illustrated in Figure 3. Although we do not find evidence of final wind curtailment due to the policy change (see Figure 2b), it is possible that wind farms bid more strategically after the change in subsidy structure once they were exposed to the market price. These more calculated bidding habits could have removed the burden on the grid operators inflicted by a large mass of 0 EUR/MWh bids offered with little regard to the wind farms' actual final generation.

The effect seen in in Figure 4 can be extended beyond exclusively 0 EUR/MWh bids. We repeated the calculations for any bids below 5 EUR/MWh and 10 EUR/MWh to graph the distribution of wind farm generation offered below 5 and 10 EUR/MWh. The results are shown in Figures fig:bidding5 and A.4, respectively. Here too, there is a significant difference in the number of hours in which 100% of generation was offered below the threshold price before and after the policy change.

The reduction in operational costs in 2014 could be explained by other factors such as commodity prices, that we attempt to control in the regression. In addition, other regulatory changes throughout the sample can affect the marginal impact of wind power on operational costs. In particular, several protocol changes enabled the participation of wind farms in the balancing market, which should also contribute to the reduction of operational costs. However, these changes are not coincident with this regulatory change. Together, these market design changes highlight the importance of adapting market operations and protocols to these new sources of energy.

Daily effects The hourly regression might miss impacts of wind intermittency that spillover nearby hours, as shown in previous literature when it comes to solar photovoltaics (Bushnell and Novan, 2018). To circumvent this issue, we present the results of a daily version of equation (1) in Table A.3 in the Appendix. In this table, the dependant variable is total operational costs in thousands of euros and the unit of observation is a day in our sample. We find that the marginal impact of wind power is consistent with our hourly estimates, with an effect of around 6,290 EUR of costs for each additional daily GWh of wind. Rescaling by average demand, this translates into an impact of around 0.22 EUR/MWh. We also find that solar power tends to increase the operational costs in the system, the same way that wind does, although these effects are very noisily estimated due to the lack of variation in solar generation within a month as well as the relatively modest levels of solar generation during our period of study. In this version of the regression, daily demand no longer has a statistically significant impact on operational costs.

Wind endogeneity We use forecasted wind as our wind variable W_t for several reasons. First, market clearing procedures often depend on forecasted wind, rather than the (unknown) realized wind. Second, using forecasted wind circumvents the issue of endogeneity of final wind production, which might be impacted by curtailment and strategic behavior. Figure 2b shows evidence that indeed final wind production can reflect endogenous curtailment. As can be observed, realized wind can be low at high levels of forecasted wind production, which tends to be reflective of forced curtailment.

We explore in Table A.4 in the Appendix the sensitivity of our results to using final wind production as well as using wind forecast and wind power as an instrument to final wind production.[9] One can see that the estimated impacts of wind either using forecasted wind power, or wind power instrumented with forecasted wind power, are analogous. However, the impact of realized wind, without correcting for endogeneity, are somewhat smaller. The direction of the bias is intuitive. By using realized wind, we are attributing some days with operational challenges and curtailment to "low wind" observations, attenuating the relationship between wind and operational costs. However, it is precisely the presence of wind that could have triggered these conditions. The instrument corrects for this bias.

Spline regressions Equation (1) assumes that the impact of wind is constant regardless of the level of generation. To explore the potential for non-linear impacts, we consider the following spline specification:

$$Y_t = \beta_0 + \sum_{q=1}^{5} \beta_q W_{qt} + \gamma X_t + \epsilon_t \ , \tag{2}$$

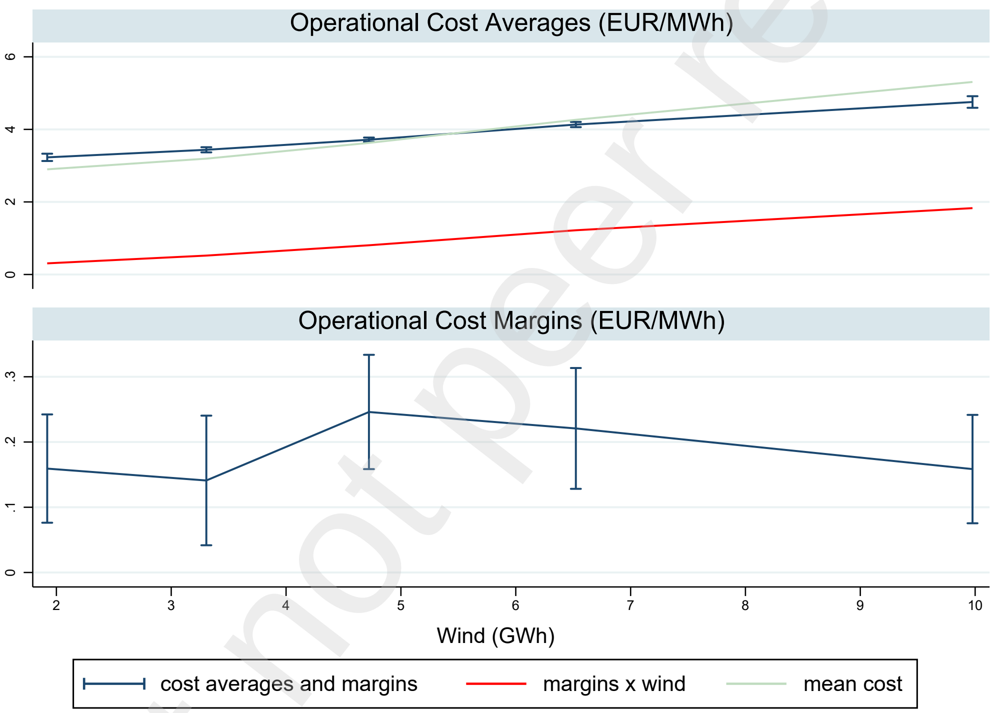
where W_{qt} are spline bins according to the quintiles of the wind variable.[10] This spline specification allows for flexible marginal effects from wind production while ensuring some consistency between the estimates of the different quintiles. The coefficients β_q provide the marginal impact from wind production on the outcome of interest. See the discussion following Equation 1 for a reminder of the definition of X_t.

We also use equation (2) to predict the average outcomes at different levels of wind, holding everything else constant. Additionally, we report the cumulative changes explained by wind by integrating out the effects implied by the coefficients β_q at different levels of wind.

[9] Wind power is created using wind speed from MERRA and converted to power using a cubic rule. We multiply wind power with installed wind capacity to account for growing installed wind capacity over time.

[10] In particular, if a quantity falls within the first quintile, W_{1t} equals W_t and the rest are zero. If a quantity falls within the second quintile, W_{1t} equals to the first quintile, and W_{2t} equals the remainder output $W_t - W_{1t}$, and so forth.

Figure 5: Average Marginal Effects of Wind on Operational Costs



Notes: This figure shows the operational cost impacts at different wind levels. The upper panel shows average operational costs at different wind levels, whereas the lower panel shows the marginal total operational cost impacts. For each wind quintile, we obtain the mean of wind forecast and use it on the x-axis.

Figure 5 shows the impacts of wind on total operational costs. The upper panel shows that, on average, wind tends to increase operational costs, which range from around 3.2 EUR/MWh at low levels of wind to over 4.5 EUR/MWh at higher levels of wind. We compare our predictions to the variation in the data, and find that the wind power, even after controlling for confounding factors, is estimated to explain most of the cost increases. We find that most of the correlation between operational cost increases and wind production can be attributed to wind generation. This is shown by comparing the "mean costs" observed in the data to those predicted by the wind quintiles. Overall, the incremental cost of wind generation on operational costs is roughly 2 EUR/MWh at the highest quintile of production.

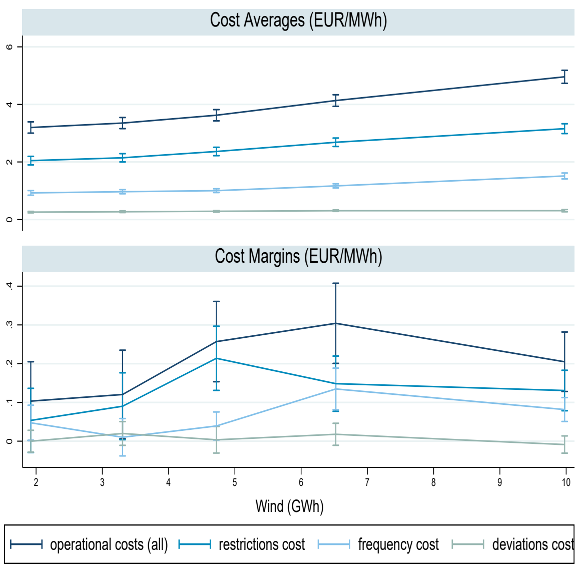
The lower panel focuses on the marginal slope implied by the spline function. We find that the marginal impacts of wind do not worsen with higher levels of wind generation. If anything, our results are more consistent with an inverted U-shape pattern. The marginal impact of wind on operational costs are relatively minor at low levels of wind, somewhat larger in middle ranges of production, and lower at the highest production levels. One possibility for this finding is that, at high levels of wind generation, many natural gas power plants are able and eager to participate in reliability markets, whereas at middle ranges of wind generation, the competition to provide reliability services might be less fierce.

Categories of operational costs We further decompose the impacts of wind on operational costs across restrictions, frequency, and deviations costs. Figure 6a shows the average marginal effects of wind on the different components of operational costs using the definition in equation (2). The impact on deviations costs is very limited given that these are the deviation costs caused by consumers, not those caused by wind firms, which are represented in Figure 6c. For higher levels of wind integration, marginal increases in wind have a higher impact on restrictions and frequency costs. To guarantee system reliability, wind plants need to be secured by surrounding power plants, which may create extra technical restrictions for higher integration levels. At the same time, the power system has to procure enough reserves to avoid insufficient generation. These reserve needs are more noticeable in days with higher levels of wind integration. Therefore, it is not surprising that deviations costs are marginally increasing as wind penetration expands.

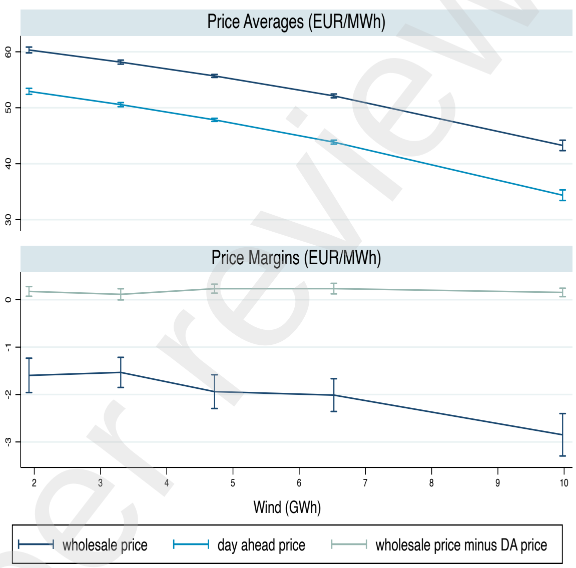
3.2 Market prices

In addition to our analysis of operational costs, we assess the impact of wind on market prices. It is well known that wind tends to reduce electricity market prices, due to its very low marginal cost of operation. To consider the broader market impacts of wind, we consider both the day-ahead market price of electricity as well as the final price of the wholesale electricity market, which includes pro-rated capacity and reliability costs as a markup. These different prices are indicated

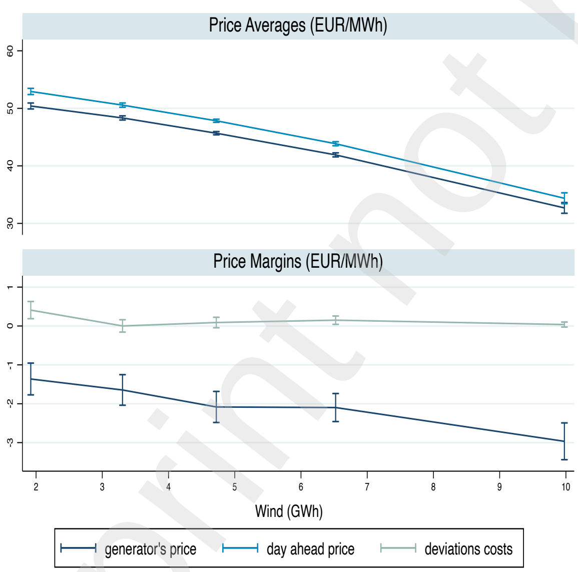
Figure 6: Impacts of Wind on Major Market Outcomes



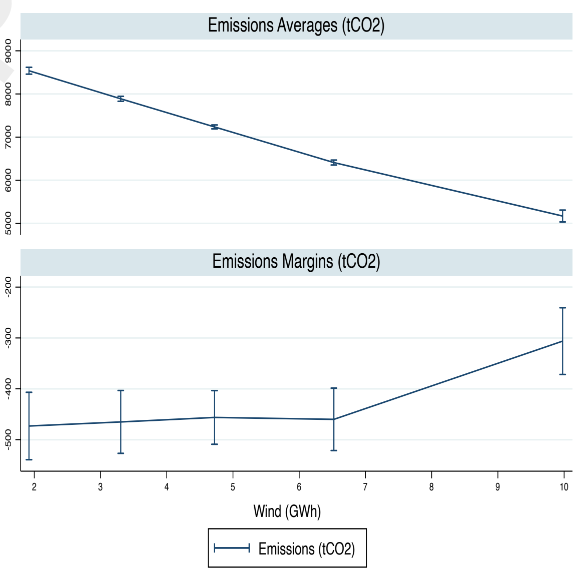
(a) operational Costs



(b) Market prices



(c) Wind Profitability



(d) Emissions

Notes: This figure shows the impacts of wind on several market outcomes. For each wind quintile, we obtain the mean of wind forecast and use it on the x-axis.

in Figure 6b as day ahead price and wholesale price, respectively.

The downward sloping average prices and the negative margins in Figure 6b are clear indications of wind's tendency to reduce electricity prices. However, the marginal difference between day-ahead and wholesale price is positive across the wind quintiles, suggesting that more wind production has a positive effect on the cost markup. This aligns with our earlier findings, which suggested that increasing wind production rises most cost components.

3.3 Wind revenues

In addition to market-wide costs, wind generators have to pay for the costs of their own last-minute deviations due to their intermittent nature. The price the generators receive, the navy line in the upper panel of Figure 6c, is therefore lower than the day-ahead market price. The teal line in the bottom panel of Figure 6c represents the marginal impact of wind on the difference between the two market price variables of interest, for which wind deviation costs can proxy. We find that the marginal costs of intermittency to wind farms are not significantly increasing with the level of wind, and if anything, they can be decreasing. The marginal impacts are small, and even insignificant at some wind levels. Deviation costs paid by consumers do not include the impact of wind, so it makes sense that they are not explained by wind (Figure 6a). When it comes to their own costs (Figure 6c), they are pretty flat and highest for low output. One potential explanation is that, with low output, deviations are more likely (variance is higher per unit of output, with a lot of wind, variance is higher but not in per unit of output terms). The availability of more idle thermal generators to compete in the deviations market during high wind hours also should help reduce marginal operational costs.

3.4 Emissions

Our final market outcome of interest is carbon dioxide emissions. We expect that as wind generation increases, emissions in the Spanish Electricity Market will decrease, due to direct substitution of wind for fossil fuel energy sources. Figure 6d demonstrates this downward trend in CO_2 emissions. We find that the marginal impact of an additional GWh of wind generation is around -500 tCO_2 across most values of wind, which is consistent with an average value of marginal emissions rates of coal (around 900 tCO_2/GWh) and natural gas generators (around 350 tCO_2/GWh).[11] However, at high levels of wind, carbon emissions in the Spanish Electricity Market decrease on average by only 60% of the margin seen at low wind levels. The marginal effect of 1 GWh of wind decreases in absolute value to approximately -300 tCO_2. This decline can be explained by a decrease in the

[11] In a separate analysis utilizing generation sources as response variables, which can be provided upon request, we confirm that this is based on a substitution of primarily coal and combined cycle generation.

substitution of coal, wind curtailment as shown in Figure 2b, as well as a corresponding increase in electricity exports. It is important to note that we do not quantify the emissions benefits of exports. If these exports offset high-emission sources in other countries, then at the global level, the marginal impacts on emissions reductions could be larger.

Intermittency decomposition We further decompose the impact of the two sources of wind intermittency - volatility and uncertainty - on the outcomes of interest. We consider the following regression specification:

$$\mathrm{Y}_t = \lambda + \sum_{q=1}^{5} f_q(V_t, U_t) W_{qt} + \gamma X_t + \psi_t \ , \tag{3}$$

where V_t and U_t are volatility and uncertainty, respectively, $f_q(V_t, U_t)$ is a parametric form describing how volatility and intermittency impact the marginal effects of wind, and W_{qt} is the spline wind variable by quintile as defined in (2). Similar to equation (2), we also allow the coefficients to depend on the wind quintile as denoted by the index q.

The function $f_q(V_t, U_t)$ allows operational costs to be explained by wind through intermittency. That is, the interaction terms between wind and wind intermittency account for the fact that both volatility and uncertainty are a function of the level of wind and jointly determine operational costs. We consider the following parsimonious specification at each quintile:

$$f_q(V_t, U_t) = \beta_{q0} + \beta_{q1} V_t + \beta_{q2} U_t, \tag{4}$$

in which we allow the impacts of wind to be potentially different in days of high volatility or high uncertainty. To investigate the impact of volatility and uncertainty, we estimate Equation 3 combined with the above intermittency specification, then examine the marginal impact of wind at various percentiles of the volatility and uncertainty distribution. We use intermittency metrics using the definitions in Section 2 and a time period of 24 hours.

Figures A.2a and A.2b in the Appendix show the results of our intermittency analysis. In Figure A.2a, uncertainty seems to have no impact on cost margins and averages at low levels of wind, and only minimally increases the impact of wind on costs at high levels of wind. In Figure A.2b, the opposite it true: volatility has no impact on cost margins and averages at high levels of wind, and a minimal, positive impact at low levels of wind. However, the decomposition of wind's impact on cost through intermittency primarily highlights the fact that volatility and uncertainty investigated in conjunction with wind have only a minor impact on total operational costs, due to the positive correlation between wind level and intermittency. That said, the overall additional explanatory impacts of volatility and uncertainty remain low, given that the biggest drivers of these factors are the levels of wind themselves. We therefore conclude that the overall level of production seems to be sufficient to capture the main impacts of wind.

4 Cost-benefit analysis of wind

The estimates from Section 3 can be used to understand the average marginal impacts of wind generation on economic welfare during our sample. We assess the economic impact of wind by using the following metric:

$$\text{Economic Surplus} = \text{Consumer Surplus} + \text{Producer Surplus} + \text{Emissions Benefits}.$$

To compute the change in consumer surplus, we evaluate the impact of wind on the electricity costs paid by consumers, i.e., the final price (including operational costs) multiplied by demand, plus the cost of the subsidies.[12] We perform a spline regression analogous to equation (2) but with wholesale electricity consumer costs as the dependent variable. Thus, the marginal impact of wind on consumer surplus is identified at differing levels of wind. Similarly, to compute the change in producer surplus, we consider the semi-parametric impact on the price effect and the replacement effect, as described in Abrell et al. (2019), plus the subsidy payments. Due to the sensitivity of our analysis to the chosen levelized cost of wind, we independently identify the impacts on non-wind producer surplus, and wind producer surplus. For both non-wind and wind producers, the price effect, which is a negative change in producer revenues, is the decrease in the day-ahead prices multiplied by demand. Because wind farms incur penalties for deviation and therefore receive a slightly lower price, we utilize the change in the wind generator price multiplied by demand. The replacement effect, which is the change in producer surplus due to the substitution of high marginal cost electricity sources, is proxied for non-wind producers using the day-ahead price.[13] For wind producer surplus, the replacement effect requires us to factor in the levelized cost (LCOE) of wind generation. As a measure of short-run surplus, we define wind producer surplus as wind revenue, which only includes the price effect and the subsidies paid to wind producers, due to the importance of the assumptions surrounding LCOE on our final analysis. We analyze the impact of capital costs separately.

Subsidies are a net transfer from consumers to producers.[14] To compute the subsidy to wind producers, we collect annual data on subsidy transfers to wind generators, and we divide it by annual wind output. As explained in Section 2, there was a change in regulation during the period of study. Wind producers received a subsidy of approximately 45 EUR/MWh before 2013. After 2013, we find that the added cost per MWh drops to approximately 30 EUR/MWh, as shown in

[12] It is important to note that we abstract away from the allocation of subsidy costs across different types of consumers (e.g., residential, commercial, and industrial). Such allocation of costs can affect the net gain from the policy of different types of consumers (Mastropietro, 2019; Reguant, 2019).

[13] The impact of wind on such a metric is $\frac{\partial p/\partial W}{2} + p$. We use the observed day-ahead price plus the change induced by wind to the market price divided by two.

[14] We abstract away from the cost of public funds for subsidies given that these are collected directly in the electricity sector. For reasonable values, they are not enough to change the sign of the welfare estimates.

Figure 1. In the baseline results, we consider a baseline subsidy cost of 40 EUR/MWh, which constitutes a subsidy value in line with previous studies (Abrell et al., 2019).

Importantly, in addition to the changes in consumer and producer surplus, we take into account the environmental benefits of wind production. Because the energy price in the Spanish electricity market already reflects the costs of CO_2 emissions to a certain extent via the EU-ETS mechanism (Fabra and Reguant, 2014), we only add the emissions benefits that are not directly included in the EU-ETS price. We regress net emissions costs ($(SCC - p_{CO_2}) \times emissions$) on our wind splines to obtain the reductions in emissions costs due to increased wind production.[15] As with levelized cost, the overall results of our analysis on total welfare are sensitive to the chosen social cost of carbon. We highlight this sensitivity in our assessment of the policy benefits.[16]

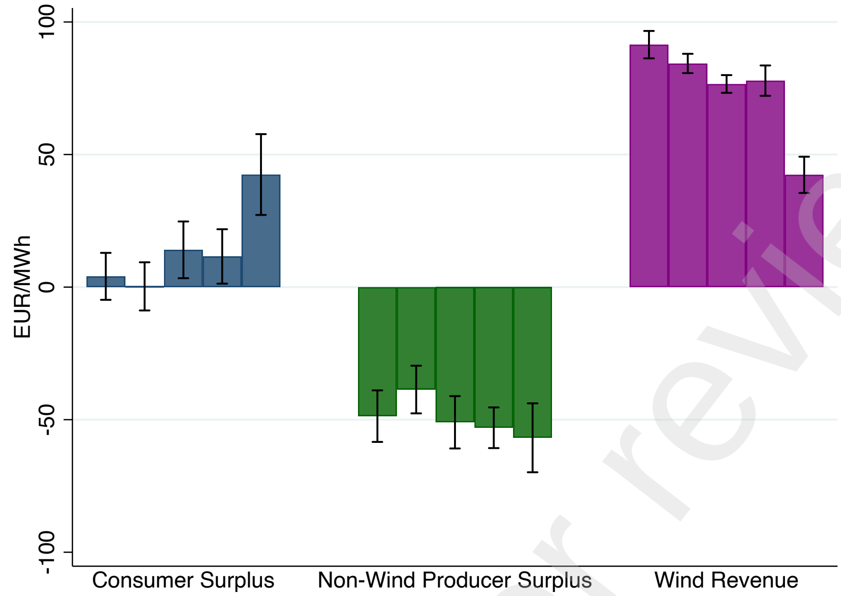
Figure 7 shows the results of our analysis for consumer surplus, non-wind producer surplus, and wind revenue at each wind quintile, with wind levels increasing from left to right within components. The impact of wind on consumer surplus (blue) is relatively small at low levels of wind, where the price effect is nearly equivalent to the cost of subsidies. However, at higher wind levels, a more dramatic decrease in electricity price is more than enough to offset the subsidies. The impact of wind on non-wind producer surplus (green) is consistently negative, due to the price effect overpowering the replacement effect. The impact of wind on wind revenues (purple) is positive but decreasing throughout the quintiles, given the cannibalization effect of wind production on wind revenues. Similar to consumer surplus, this is due to the sharp reduction in price at high levels of wind.

To analyze the overall welfare impacts, including emissions benefits and capital costs, Figure 8 shows the impact of two key variables, the levelized cost of wind and the social cost of carbon, on the results of our total welfare analysis. Depending on the choice of interest rate or the date of installation, wind farm levelized costs can easily range from 50 to 90 EUR/MWh. Additionally, the social cost of carbon is a highly debated metric, due to the uncertainty surrounding future damages and the choice of a long term discount rate. In Figure 8, we choose a high (90 EUR/MWh), medium (70 EUR/MWh), and low (50 EUR/MWh) set of levelized costs, and calculate the impact of wind on total welfare across a range of social costs of carbon. We find that at our lowest LCOE, the impact of wind on total welfare becomes positive at a very modest SCC of approximately 30 EUR/tCO_2. The medium and high LCOE specifications require larger social costs of carbon (80 EUR/tCO_2 and 130 EUR/tCO_2, respectively) to achieve a positive impact of wind on total welfare. However, all three of these "social cost of carbon cut-offs" are within the broad range of values climate scientists and economists recommend. Note that if we assume that wind farms at

[15] We obtain similar results if instead multiply the emissions marginal reductions by the average additional environmental benefit.

[16] Note that we are not considering other co-benefits of wind production, and therefore these environmental benefits could be considered lower bound on the environmental benefits of wind output.

Figure 7: Average Welfare Effects of Wind



Notes: This figure shows the impacts of wind on various welfare components. Within each component, the effect is depicted at the five different wind quintiles, starting with the smallest quintile on the left, and moving to the largest quintile on the right.

least recovered their capital costs under this policy, given that their estimated net revenues are around 55 EUR/MWh, welfare is positive as long as the value of emissions reductions is around 50-55 EUR/tCO_2, making the welfare benefits of the policy positive for costs of carbon in the lower range.[17]

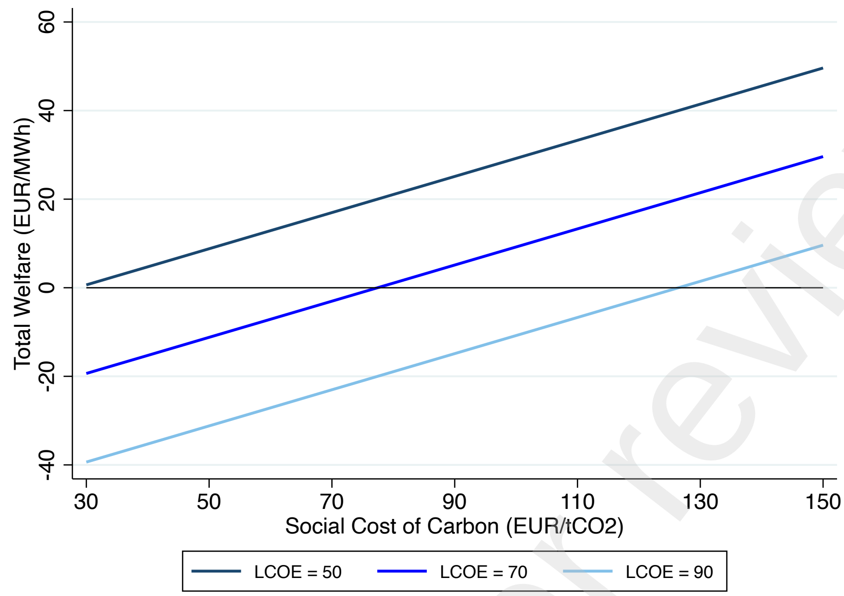
5 Conclusion

We analyze the benefits and costs of wind production in the context of the Spanish Electricity Market. We take a comprehensive approach considering not only the market price and emissions effects but also the impacts of wind intermittency on operational costs more broadly. We exploit the exogeneity of wind forecasts to show the marginal effect of wind on several relevant market outcomes. Our results demonstrate that wind and intermittency impose additional costs on the electricity grid. However, the increases in such costs are modest in relationship to the general price decreases induced by wind power.

We combine our evaluations of several market outcomes with information on government subsidies to conduct a thorough analysis of the welfare effects of wind generation. We find that, across

[17]Under this assumption, this estimate can be considered an upper bound if the wind farms entered the market with positive surplus.

Figure 8: Cost-Benefit Sensitivity Analysis



Notes: This figure illustrates the sensitivity of the overall welfare impacts of wind as a function of two key variables: levelized cost of wind, and social cost of carbon. The figure shows the "break-even" social costs of carbon (on the x-axis) of the policy intervention for different LCOE values (y-axis).

most levels of wind, both wind revenue and consumer surplus are positively impacted by the inclusion of wind power and its corresponding subsidies. Across all levels of wind, total welfare is positive, and made even larger by factoring in the external benefits of reduced CO_2 emissions. These gains make these early investments in wind power cost effective for reasonable values of the cost of capital.

Overall, our conclusion is that the negative impacts of wind on operational costs have been quite modest, even at relatively high levels of wind generation. There are different ways that the negative impacts of renewable intermittency are expected to decrease even further in the future. First, developing more accurate forecasts could reduce uncertainty. Second, power systems could contribute to a reduction in intermittency by incorporating more storage technology. Another solution is for governments to encourage the use of real time pricing or time of use rates. If consumers are responsive enough, they will internalize generation costs and possibly transfer demand to hours when energy prices are lower or when renewable production is higher.[18] Finally, active modifications to the market design can improve wind participation in organized electricity markets and reduce the operational costs from accommodating these sources of energy into the grid.

[18] While the Spanish market has emphasized some dynamic pricing regulatory changes for households, the evidence so far shows limited demand flexibility on the residential side (Fabra et al., 2021).

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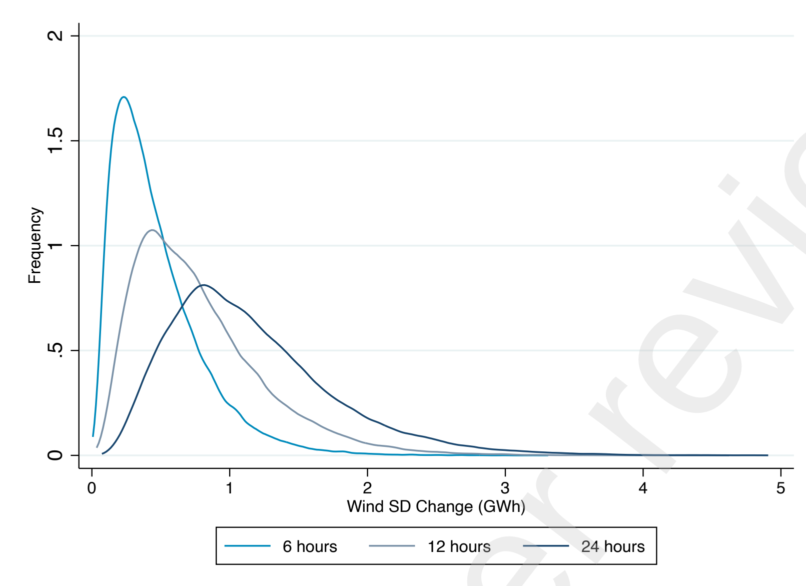
A Additional Tables and Figures

Table A.1: Regulation changes

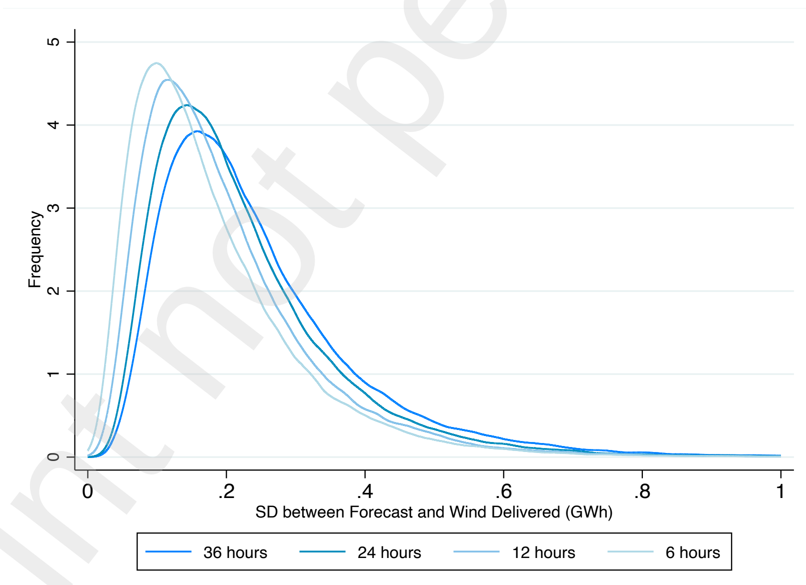
Regulation	Summary	Implications
Royal Decree-Law 1/2012 (January 2012)	Suppression of economic incentives (tariffs or premiums) for new electricity production facilities using renewable resources.	Limited installed wind capacity growth during our study period.
Royal Decree-Law 2/2013 (February 2013)	Elimination of the Feed-in-Premium (FiP) pricing scheme. Renewable producers up to this regulation could opt for two pricing schemes (a) Feed-in-Premium (FiP), or (b) Feed-in-Tariff (FiT). Under option (a), producers sold their electricity in the electricity market and their price would be determined by the market price plus a premium payment. Under option (b) or FiT, producers had to offer all their production at a zero price in exchange of a regulated compensation invariable for all scheduling periods.	Under this regulation, all producers under the FiP scheme are moved to the FiT scheme. The consequence of this regulation is that wind producers stops arbitraging intra-day markets (Ito and Reguant, 2016).
Royal Decree-Law 9/2013 (July 2013)	Renewable generators were no longer entitled to receive the two pricing schemes described in the above legislation (options (a) and (b)). This regulation in addition set up a new pricing scheme based on a reasonable compensation that was implemented in June 2014. During this period, the pricing scheme in place was the FiT scheme.	
Royal Decree-Law 413/2014, Orden IET/1045/2014 (June 2014)	Implementation of new pricing scheme for renewable producers already announced in the regulation of July 2013. The new compensation was based on installed capacity rather than produced electricity. It was calculated as the sum of a capacity payment to compensate investment costs not recovered through the market, and a production payment to provide investment incentives by reducing production costs. This regulation in addition stated the possibility of renewable sources' participation in adjustment markets (their participation effectively started in February 2016).	The new pricing scheme applied to facilities that had not recovered the investment costs previously (mostly capacity installed after 2005). Around 51% of the installed wind capacity was exposed to market prices as the lower subsidies would not compensate their operating costs. This exposure increased market prices, as renewable producers offer their production at least at their operating cost (no longer at zero prices). In addition, the participation of wind in adjustment markets in 2016 lowered prices in those markets.

*https://www.cnmc.es/sites/default/files/editor_contenidos/Energia/Consulta%20Publica/20190627_6_Informe%20Justificativo_POs_MIC%2015h-Tras%20Consulta%20P%C3%BAblica.pdf

Figure A.1: Distribution of wind intermittency



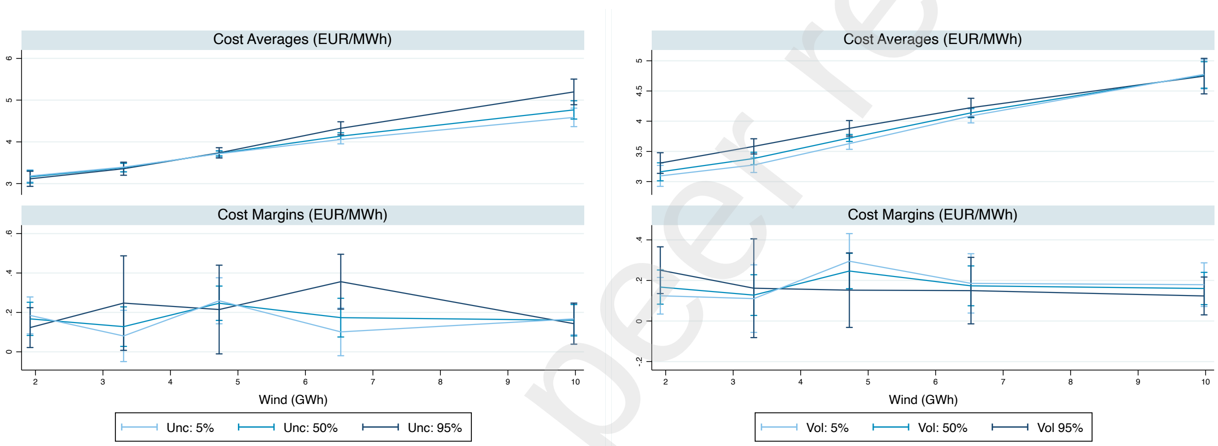
(a) Volatility



(b) Uncertainty

Notes: This figure shows two measures of intermittency: volatility and uncertainty. Volatility is defined as the standard deviation of changes in wind production during a certain length of time. We have computed volatility for 6, 12, and 24 hours output differences. Uncertainty is defined as the standard deviation of forecast departures from final wind delivered in the last H hours before production. We have computed uncertainty for 6, 12, 24, and 36 starting times. The distribution of uncertainty has been truncated at 1 GWh for improved readability.

Figure A.2: Impact of uncertainty and volatility on system costs



(a) Uncertainty Decomposition

(b) Volatility Decomposition

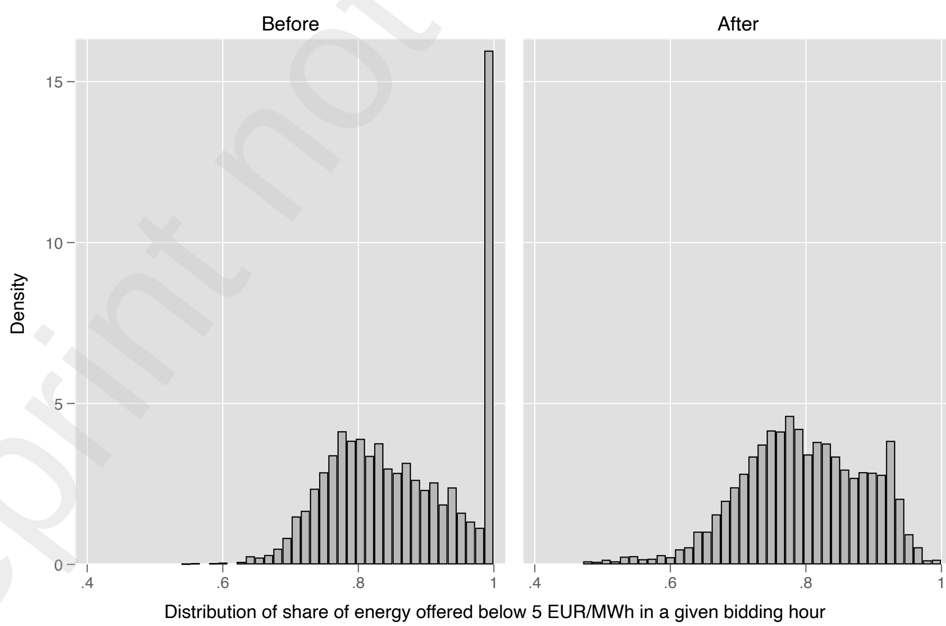
Notes: This figure compares the impact of wind on total system costs at different levels of uncertainty and volatility. The upper panel (Cost Averages) shows the average system costs impacts, whereas the lower panel (Cost Margins) shows the marginal effects. Volatility is analyzed at its 5th, 50th, and 95th percentiles, while uncertainty is maintained at its 50th percentile. For each wind quintile, we obtain the mean of wind forecast and use it on the x-axis. Uncertainty is analyzed at its 5th, 50th, and 95th percentiles, while volatility is maintained at its 50th percentile. For each wind quintile, we obtain the mean of wind forecast and use it on the x-axis.

Table A.2: Sensitivity to fixed effects of marginal impacts to operational costs

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Forecasted wind (GWh)	0.234	0.215	0.222	0.176	0.225	0.191
	(0.0206)	(0.0185)	(0.0222)	(0.0178)	(0.0223)	(0.0162)
Forecasted demand (GWh)	-0.0741	-0.0467	-0.0702	-0.0396	-0.173	-0.157
	(0.0235)	(0.0215)	(0.0228)	(0.0215)	(0.0219)	(0.0188)
Solar production (GWh)	-0.241	-0.264	-0.359	-0.410	-0.433	-0.0124
	(0.0579)	(0.0510)	(0.0581)	(0.0532)	(0.155)	(0.0645)
Observations	83,840	83,840	83,840	83,840	83,840	83,840
R-squared	0.129	0.241	0.151	0.338	0.240	0.561
Year FE	No	Yes	No	Yes	No	Yes
Month FE	No	No	Yes	Yes	Yes	Yes
Hour FE	No	No	No	No	Yes	Yes

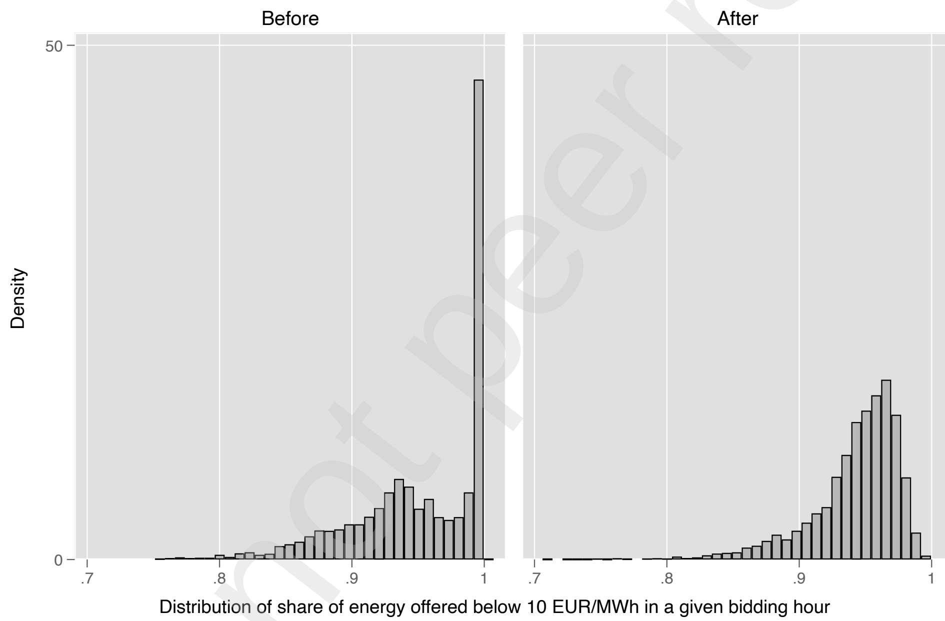
Notes: Standard errors clustered at the month of sample. All regressions include demand forecast, natural gas prices, temperature, temperature squared, dew point, and solar production as controls.

Figure A.3: Distribution of Wind Levels Bid below 5 EUR/MWh, Before and After June 2014



Notes: Own elaboration based on hourly unit-level bidding data from the Iberian Electricity Market Operator (OMIE) during the year of 2014. We select production units that are linked to wind farm operations before examining the data.

Figure A.4: Distribution of Wind Levels Bid below 10 EUR/MWh, Before and After June 2014



Notes: Own elaboration based on hourly unit-level bidding data from the Iberian Electricity Market Operator (OMIE) during the year of 2014. We select production units that are linked to wind farm operations before examining the data.

Table A.3: Daily marginal impacts to operational costs

VARIABLES	(1)	(2)	(3)	(4)
Forecasted wind (GWh)	6.131	6.128	6.282	6.152
	(0.457)	(0.457)	(0.457)	(0.476)
Forecasted demand (GWh)	0.0339	0.00405	-0.112	-0.0955
	(0.543)	(0.531)	(0.528)	(0.533)
Solar production (GWh)	8.406	8.703	8.451	6.104
	(5.150)	(5.098)	(5.330)	(6.439)
NG price (EUR/MWh)		11.29	5.375	4.859
		(26.87)	(26.31)	(26.16)
Mean temperature (F)			-60.67	-49.69
			(38.08)	(41.20)
Sq. mean temp. (F/1000)			370.0	313.4
			(289.1)	(299.3)
Mean dew point (F)				-4.484
				(7.502)
Observations	3,507	3,507	3,507	3,507
R-squared	0.683	0.683	0.686	0.686
Implied average effect	0.214	0.214	0.219	0.214

Notes: Standard errors clustered at the month of sample. All regressions include month of sample fixed effects. The dependant variable is the daily sum of operational costs in thousands of euros.

Table A.4: Impact of wind vs. forecasted wind

VARIABLES	(1) Wind Forecast	(2) Wind	(3) IV Forecast	(4) IV Power
Forecasted wind (GWh)	0.191			
	(0.0162)			
Final wind production (GWh)		0.152	0.182	0.188
		(0.0140)	(0.0150)	(0.0189)
Observations	83,840	83,841	83,840	81,348
R-squared	0.561	0.557	0.079	0.079

Notes: Standard errors clustered at the month of sample. All regressions include demand forecast, natural gas prices, temperature, temperature squared, dew point, and solar production as controls.

Table A.5: Wind production and wind power after policy change

	(1)	(2)	(3)	(4)
VARIABLES				
Wind power before	0.936	0.935	0.932	0.895
	(0.137)	(0.133)	(0.132)	(0.131)
Wind power after	1.155	1.153	1.154	1.107
	(0.0838)	(0.0842)	(0.0864)	(0.0883)
Forecasted demand (GWh)	0.00536	0.00479	0.00865	0.0118
	(0.0209)	(0.0204)	(0.0187)	(0.0192)
Solar production (GWh)	-0.274	-0.278	-0.145	-0.601
	(0.123)	(0.125)	(0.151)	(0.184)
NG price (EUR/MWh)		-0.167	-0.161	-0.150
		(0.119)	(0.116)	(0.114)
Mean temperature (F)			0.136	0.270
			(0.0526)	(0.0691)
Sq. mean temp. (F/1000)			-1.398	-2.007
			(0.402)	(0.506)
Mean dew point (F)				-0.0726
				(0.0200)
Observations	16,557	16,557	16,557	16,557
R-squared	0.770	0.771	0.774	0.782

Notes: Standard errors clustered at the month of sample. All regressions include month of sample fixed effects. The dependent variable is wind production in GWh. The sample only includes a year before and after the policy change, June 2013 to May 2015.