Measuring the Impact of Wind Power and Intermittency*

Claire Petersen† Mar Reguant‡ Lola Segura§

October 2, 2023

Abstract

Wind power is crucial to decarbonizing electricity markets but is intermittent, which complicates operational management. We assess the welfare impact of wind power on the Spanish electricity market during the years 2009-2018, with a focus on how wind impacts congestion and reliability costs. In the baseline results, for an additional GWh of forecasted wind generation, we estimate that operational costs go up by about 0.19 EUR/MWh compared to an average of 3.85 EUR/MWh. We find no evidence of these marginal impacts significantly increasing with wind availability. Using detailed bidding data for congestion and reliability markets, we highlight how changes in market design can reduce the negative impacts of wind power on the operation of the grid.

KEYWORDS: electricity markets, energy transition, intermittency, wind power.

JEL classification codes: Q40, Q42, Q52.

*Reguant acknowledges the support of NSF grant SES-1455084. This project/article has received funding from the European Research Council (ERC) under the European Union's Horizon 2020 research and innovation programme (grant agreement No 101001732-ENECML). We thank Sarrin Chethick, Matthew Stadnicki, and Tomas Wilner for excellent research assistance. A public repository with replication data and code can be found at https://github.com/mreguant/wind-costs-intermittency.

†Cambridge University. E-mail: cjp89@cam.ac.uk.

‡Northwestern University and Barcelona School of Economics. E-mail: mar.reguant@northwestern.edu. Corresponding author.

§Analysis Group, E-mail: Lola.SeguraVaro@analysisgroup.com.

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).

The detailed, high-frequency available data for the Spanish electricity market, as well as the widespread integration of wind, makes Spain's electricity market a unique opportunity to evaluate the impact of wind at high generation levels. 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. 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 excess wind, 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 from 2008-2019. 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 payments for installed capacity, subject to availability requirements. This regulatory change shifted the bidding behaviour of wind generators - eliminating instances in which 100% of wind farms bid full generation at 0 EUR/MWh, and thus reducing the need for forced curtailment. Using an annual regression, we find that the marginal impact of wind on operational costs was reduced after the market changes by approximately 0.1 EUR/MWh per 1 GWh of wind.

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 either equals or outweighs the negative cost associated with paying for subsidies, depending on the wind level. 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. The consumer surplus and wind producer surplus would be higher if operational costs were not increased due to wind integration. However, the central estimates for the marginal impact of wind on welfare measures are not statistically significantly different with and without integration costs.

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. Following the previous welfare analysis, if the marginal impact of wind integration on operational costs were negligible, then the value of emissions reductions required for positive welfare would be smaller. Given the high need for decarbonization and recent updates in the social cost of carbon (Newell et al., 2022; 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. (2018), 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 et al. (2020), 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 (2021) (California) and Gelabert et al. (2011) (Spain) find that overall, renewables decrease electricity prices. However, Bushnell and Novan (2021) determine 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) find 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) evaluate 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, several papers evaluate the shift in subsidy payments that occurred in Spain. Exploiting similar time-series variation, Ito and Reguant (2016) show that wind farms substantially change their behavior in sequential markets when the premium is removed in 2013. Fabra and Imelda (2021) also examine how this change and the subsequent 2014 change affected electricity market prices and bidding behavior. Differently, we focus on the evolution of operational costs and wind curtailment. Ciarreta et al. (2020) look 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 reduced price volatility, even though renewable generation increased.

In addition, other papers study similar policy changes in wind subsidies. Aldy et al. (2023) use 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. A similar policy change for the US is studied by Johnston (2019), with a focus on how the tax treatment of the different subsidy mechanisms affects investment. A relevant difference in our setting is that Spain's changes in subsidies affect already installed plants, and therefore the investment margin is not relevant in our setting. When it comes to production, we would expect firms under the fixed fee to always offer their quantity. Firms receiving a premium are also likely to offer all of their output in order to receive the premium (even if prices are at its floor of zero). However, after 2014, many wind farms were not subsidized at all, in which case they could be more responsive to the market price, which stopped being zero. We examine the overall effect on operational costs that arise from the subsidy design, which is a novel focus. However, because our variation is only in the time series, we need to be cautious in its interpretation.

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, with an emphasis on operational costs. 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.

In these sequential markets, producers participate by adjusting 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 are used to handle these operational needs, namely four, the restrictions market, the frequency market (secondary and tertiary), and the deviations market. These markets can be differentiated based on their function, as well as when they occur with respect to the time of delivery. The restrictions market takes place first, ie., many hours before the electricity is actually delivered. It takes into account congestion offered in the day-ahead market. Second, the frequency market provides reserves or back-up capacity to respond to unexpected deviations in demand or production. Firms in the frequency market offer their power plants to provide reserve services and get compensated on an individual basis. These services have been 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). 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 uncertainty and therefore deviations in demand or renewable generation, rewarding firms that adjust their production on an individual basis to ensure that demand and supply match.

The prices for these services are determined in each of the four separate markets: restrictions (MWh), secondary band (MW) and tertiary reserves (MWh), and the deviations market (MWh). The restrictions market is solved as a pay-as-bid auction, due to the idiosyncratic nature of solving for congestion and other relibaility needs. The other markets are solved mainly as a uniform auction.[2]

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

[2] In reality, the market can have up to four separate prices, as the quantities are procured in four regions to ensure

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 deviation costs). Intermittency costs directly paid by wind producers are captured by "Costs to Wind". Data from 2009 to 2018. $N = 83,840$.

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. The penalty of these last minute deviations is determined by the ability of other generators to make up for the loss. The penalty is by construction at least equal to the market price, and oftentimes larger. If wind farms generate more electricity than scheduled, they get a payment for their surplus energy, but it is at 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 and to which extent these costs are borne by the wind farms. 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 deviation 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.

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

that the system is in balance.

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 deviation 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 the gross profits.

2.2 Data

We construct a dataset using publicly available data from the system operator, Red Eléctrica de España (REE), and 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 has a 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 REE and OMIE datasets include hourly bidding offers at the generator level, allowing us to monitor bidding behaviour over time not only in the day-ahead market, which is more common, but also in the other complementary markets. 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.[3] Prior to March 2010 we utilized the British Virtual Gas Hub Spot Price, 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[4] (prior to 2017) and the Tutiempo databases[5] (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.[6]

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

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

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

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

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 the average hourly wind production of 5.34 GWh.

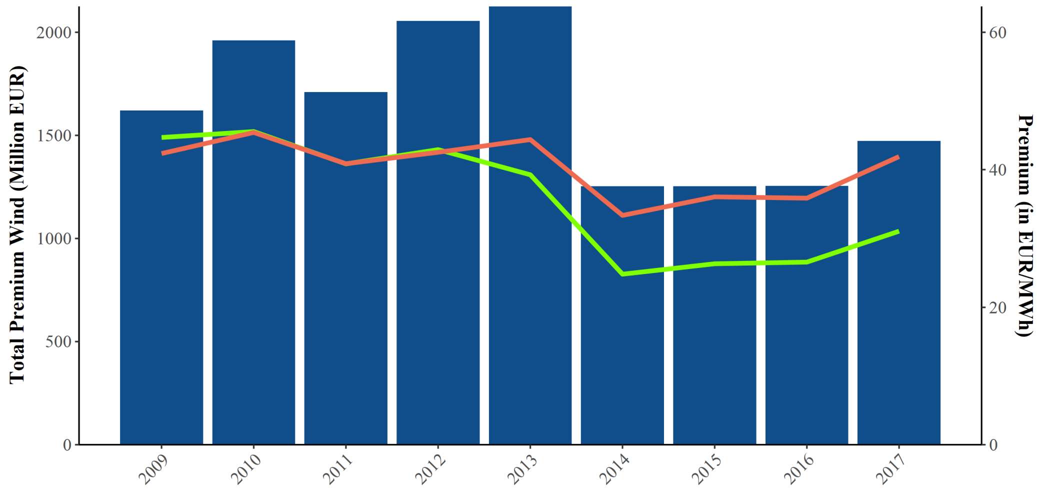
We define uncertainty as the difference between forecasted and actual generation. We compute uncertainty as the standard deviation of the differences between forecasted and delivered wind in the periods leading to the time of delivery. We exploit the fact that we observe predicted wind at different intervals: 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.

2.3 Regulatory changes surrounding wind power

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

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 (left axis - millions of EUR) and the implied subsidies (right axis - 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).

to 18.9% in 2014.[7] 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 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 between 2009

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

and 2013, down to an average subsidy of 30 EUR/MWh between 2014 and 2017.

The first regulation in 2012 suppressed the economic incentives for new renewable production facilities, causing renewable capacity to stop 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 and, thus, where not directly competing in the day-ahead market. In July 2013, the government further eliminated the FiT pricing scheme and brought wind farms back into the day-ahead market, although the new pricing scheme was not implemented until June 2014. These new regulations affected the arbitrage incentives for wind plants and market power (Ito and Reguant, 2016; Fabra and Imelda, 2021).

With the regulatory change 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 their 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 of the scheme and sacrifice the subsidy to receive the market price instead.[8]

Figure 2 explores wind behavior during this policy change. Going from production-based to capacity-based subsidies removes the incentives to bid all wind production at very low prices. As a result of the policy change, more wind farms no longer offered their generation to the market at 0 EUR/MWh, and instead chose to set their bids higher. We collect 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. Panel 2a illustrates the density of these percentages before (Jan-May 2014) and after (June-Dec 2014) the June 2014 regulatory change. Before the policy change, nearly 15% 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.[9]

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

[9]The effect seen in Panel 2a 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 A.2 and A.3, 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.

There are several reasons why wind farms no longer bid zero at the margin. First, wind farms face some marignal costs, even if low. There is some wear and tear that is estimated to be around 5 EUR/MWh. Additionally, if they overrepresent their expected quantity, they might end up paying penalties. Deviation penalties can imply negative expected revenues when prices are zero or very close to zero. Thus, one would expect them to not bid exactly zero at the margin in the absence of a subsidy. When there is a subsidy added to the market price, however, the margin to make positive profits is larger, and therefore it is more frequent that firms bid zero.

Wind farms bidding less aggressively in the day-ahead market is in line with the day-ahead marginal prices observed before and after the policy change, which stopped having a mass point at zero, as shown in Panel 2b. The policy change reduced the occurrence of zero prices in the wholesale electricity market to virtually zero.

The June 2014 policy change also appears to have reduced forced wind curtailment as well, especially for the large outliers, as shown in Panel 2c. This suggests that the regulatory change reduced the incentives for wind farms to offer their output in the market in situations of wind oversupply. It is likely that reductions in maximized output and wind oversupply would lead to a reduction in congestion, and thus a reduction in operational costs in the restrictions market.

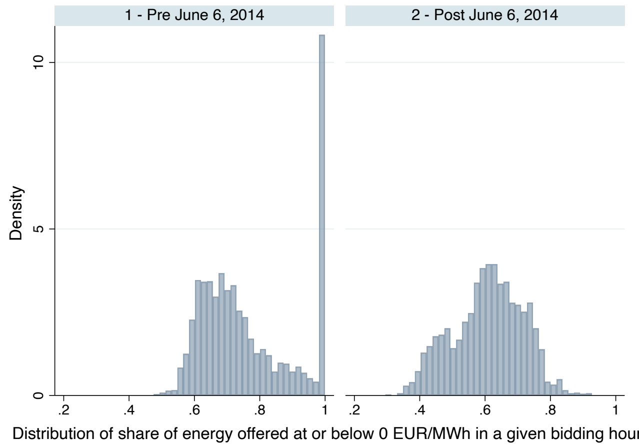
In addition to this change in bidding behavior, the regulatory change also considered allowing wind farms to participate in secondary reserve markets, which became effective in February 2016. This change in market design could also potentially ease the operational costs from having wind power, by allowing wind farms to provide a new service and compete with other potential suppliers. Due to the nature of wind power, wind farms could only provide this service in the direction of going down (voluntary curtailment). The wind farm assiciation (AEE) stated: "The improvement in wind forecasting for the operation of balancing services facilitates their participation while reducing their deviation costs. This introduces more competition in the markets and minimizes the system's deviation cost." These highlighted policy shifts illustrate how changes in the market rules can potentially reduce the costs of wind integration, something that we explore in the regression analysis below.[10]

3 Quantifying the impact of wind

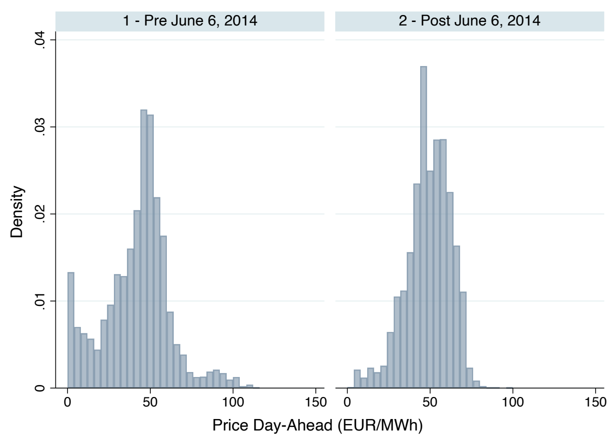
We empirically investigate the impact that wind power has had on the operations of the Iberian electricity market. Our goal is to characterize the impacts that wind generation has on several market outcomes, such as prices, operational costs, and carbon dioxide emissions, putting special

[10]The move towards much more frequent clearing of markets (going from one-hour intervals to fifteen-minute intervals) is another example of market design changes triggered by the presence of more intermittent generation. We do not explore this policy change because it occurs outside of our sample, in 2022.

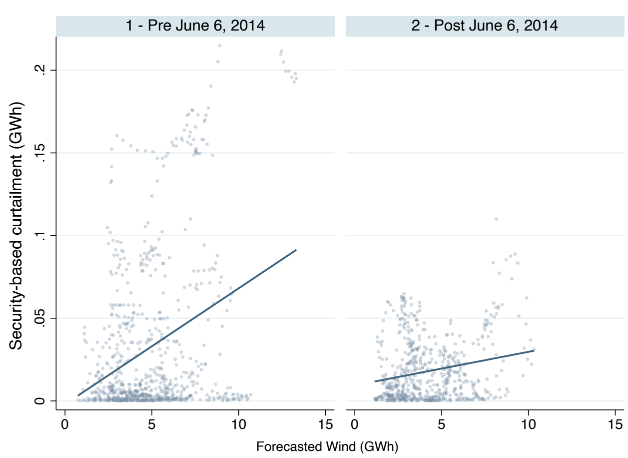
Figure 2: Bidding, price and curtailment outcomes before and after the 2014 policy change



(a) Share of wind power bid at 0 EUR/MWh



(b) Day-ahead marginal prices



(c) Wind curtailment

Notes: Own elaboration based on hourly market and unit-level bidding data from the Iberian Electricity Market Operator (OMIE). Sample June 2013-June 2015.

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, such as congestion payments and reliability services, which are very directly linked to intermittency. We then report other market outcomes that are relevant for a comprehensive cost-benefit evaluation (prices, wind revenues, and emissions), which we perform in Section 4.

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:[11]

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

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 suggest 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

[11] 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.

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 in providing these balancing services, although the effects are noisily measured due to the inclusion of substantial fixed effects.

In Table 2, demand is negatively related to operational costs, due to the fact that the dependent variable is in units of EUR/MWh. Initially, one might expect that with more energy to be managed the operational costs would increase, thus yielding a positive coefficient on forecased demand. However, as demand increases, the total MWh that must be supplied increases, and thus the costs per MWh decrease, yielding a negative coefficient.[12] We do not believe that increasing wind generation would similarly result in negative β_1 values when regressing against outcomes of interest measured in EUR/MWh as demand does, because wind is a reasonably small percentage of total generation and is uncorrelated with demand.

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 (2021) 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. These different point estimates only leave the 95% confidence range of the central estimate when the year fixed effects are removed - strengthening our argument for a shift in the marginal impact of wind on operational costs over time. In future regressions, we maintain month-of-sample interacted with hour 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,

[12] A large part of this effect is driven by hourly changes in demand. This "economies of scale" hypothesis is indirectly tested in Table A.4, in which daily operational costs, in thousands of euros, is the dependent variable rather than hourly operational costs in EUR/MWh. Here, the coefficient on forecasted demand is no longer significant and has a much smaller magnitude than the coefficient on wind, which is still significantly positive.

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.

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. The magnitude of the negative coefficient associated with demand becomes smaller, because peak demand hours with high operation cost are now explained by the demand variable rather than the hourly fixed effects. Wind effects, on the contrary, are robust to fixed effects due to the inherent randomness of wind output, which is not true for electricity demand and solar generation.

Sensitivity to wind endogeneity We use forecasted wind as our wind variable W_t for several reasons. First, market clearing procedures for the day-ahead and reliability markets are based 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 behavior. For example, realized wind can be low at high levels of forecasted wind production, if curtailment occurs. That said, forecasted wind can incorporate some of the expected behavior, e.g., the operator can anticipate some market-clearing effects. Therefore, we also consider exogenous wind speed as an alternative instrument.[13]

We explore in Table A.3 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 for final wind production. One can see that the estimated impacts of wind either using forecasted wind power, or realized wind instrumented with forecasted wind power, are analogous. However, the impact of realized wind, without correcting for endogeneity, is 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.

Daily effects The hourly regression might miss impacts of wind intermittency that spillover to nearby hours, as shown in previous literature when it comes to solar photovoltaics (Bushnell and Novan, 2021). To circumvent this issue, we present the results of a daily version of equation (1) in Table A.4 in the Appendix. In this table, the dependent 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

[13] 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.

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.

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.

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. From the years 2009-2012, the central estimates for the operational cost margins were approximately equal to 0.3 EUR/MWh. However, starting in 2014, the central estimates were between 0.1-0.2 EUR/MWh.

The results suggest that the regulatory changes highlighted in Section 2 could have reduced the negative impacts of wind power on operational costs at the margin, potentially via a reduction in wind over-production and congestion. However, this interpretation should be taken with caution. It is important to keep in mind that the reduction in operational costs starting in 2014 could be explained by many other factors such as commodity prices and annual seasonal variations, that we attempt to control for in the regression. In addition, other time-series changes throughout the sample can affect the marginal impact of wind power on operational costs.

Quintile 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:

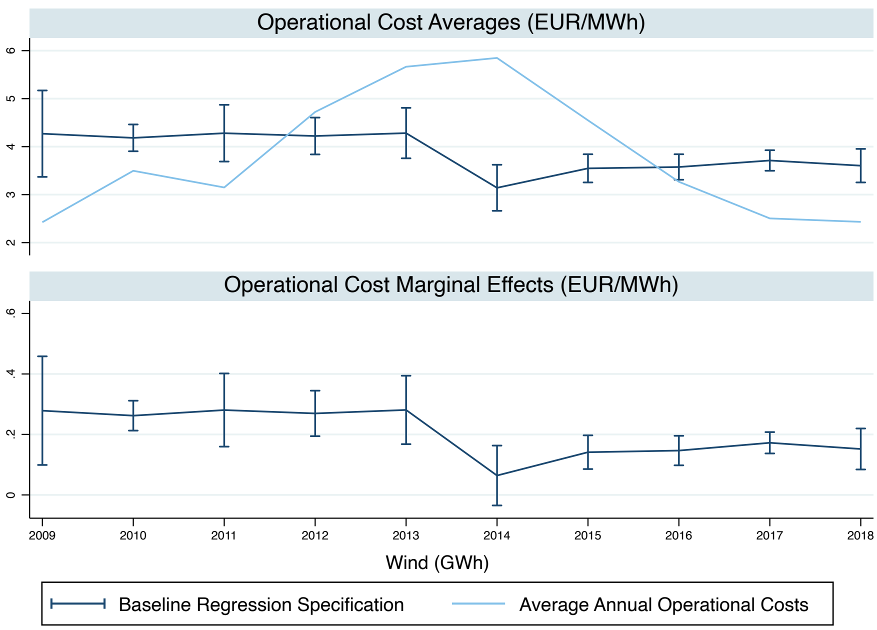
$$Y_t = \beta_0 + \sum_{q=1}^{5} \beta_q W_{qt} + \gamma X_t + \epsilon_t \ , \tag{2}$$

where W_{qt} are spline bins according to the quintiles of the wind variable.[14] 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 of 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.

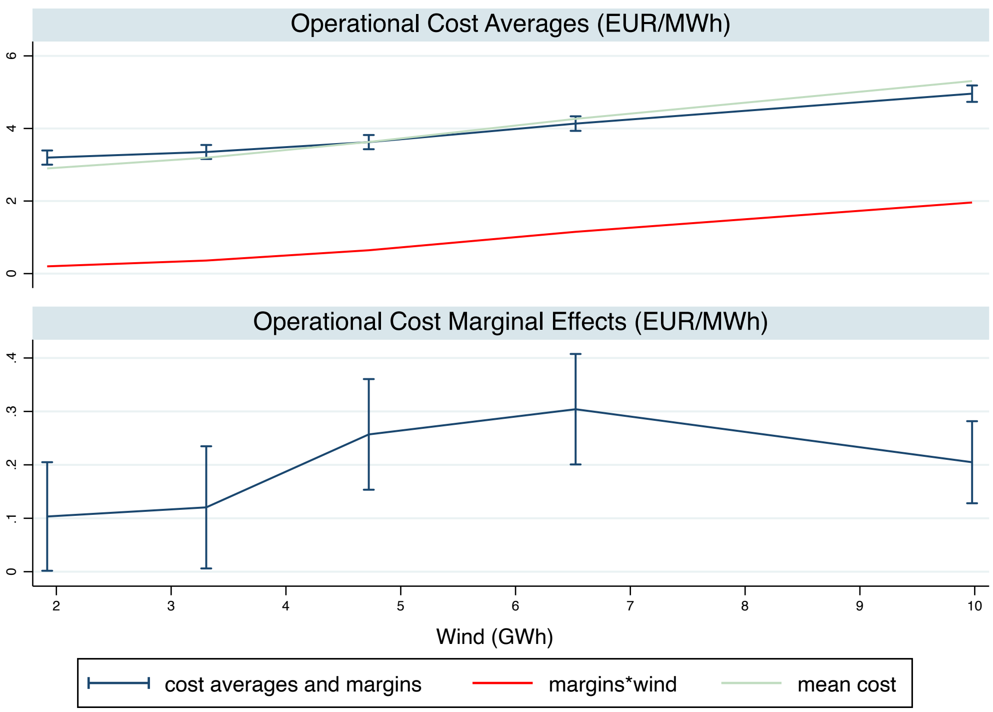
[14] In particular, if a quantity falls within the first quintile, W_{1t} equals W_t and the rest are zero. If a quantity falls within the second quintile, W_{1t} equals the first quintile, and W_{2t} equals the remainder output $W_t - W_{1t}$, and so forth.

Figure 3: Annual Average and Marginal Operational Cost Effects



Notes: The figure reports average operational costs holding everything else equal other than wind effects (upper panel) and marginal effects of wind on operational costs (lower panel), both based on equation (1). Mean annual costs are also included in the upper panel for reference. Operational costs fluctuate over the years due to commodity price shifts among other factors, which we control for when examining the impact of wind on operational costs. Marginal effects estimated from separate yearly regressions with the controls of specification (4) in Table 2.

Figure 4: 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. Calculations based on marginal estimates from spline regressions with the controls of specification (4) in Table 2.

Figure 4 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 at the higher levels of wind generation. Our results are more consistent with an inverted U-shape pattern. The marginal impact of wind on operational costs is relatively minor at low levels of wind, somewhat larger in middle ranges of production, and lower at the highest production levels. This is a key finding, as one might have expected increased wind power to make grid operations increasingly difficult also at the margin. This somewhat surprising result hides important compositional effects across different reliability products, which we explore in Section 3.2 when examining operational costs by categories.

Another potential driver of the inverse U-shape in Figure 4 is increasing levels of wind over time, which interact with changes in marginal operational costs over time, e.g., due to the improved integration of wind power into the grid. Figure A.4 in the Appendix complements the analysis with a quintile regression that is separately estimated for each year in the sample. We find that, while there is variation from year to year in the shape of the quintile impacts of wind power, the marginal impact of wind remains low at high levels of wind, and in many years we still see the inverse U-shape documented in Figure 4.

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 measures of volatility and uncertainty, respectively, $f_q(V_t, U_t)$ is a parametric form describing how volatility and uncertainty impact the marginal effects of wind, and W_{qt} is the spline wind variable by quintile as defined in Equation (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.[15] Mathematically, these definitions can be expressed via Equations (5) and (6):

$$V_t = SD\left(\{Wind_t - Wind_{t-h}\}_{h=1}^{24}\right), \tag{5}$$

$$U_t = SD\left(\{Wind_t - Forecasted\_Wind_{t-i}\}_{i=1}^{24}\right). \tag{6}$$

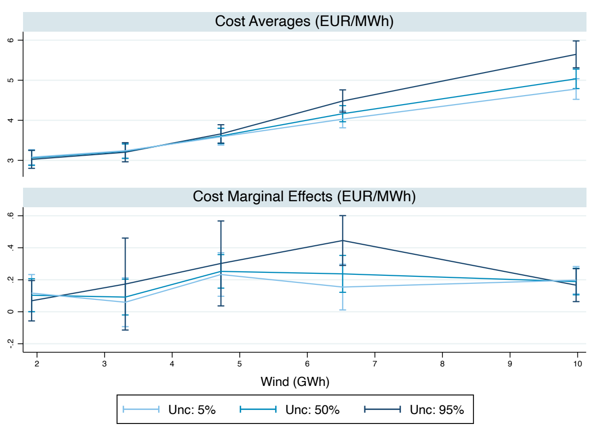
Figures 5a and 5b show the results of our intermittency analysis. In Figure 5a, uncertainty seems to have no impact on cost margins and averages at low levels of wind, and only minimally increases the impact of wind on costs at high levels of wind. In Figure 5b, the opposite is true: volatility has no 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.

3.2 Categories of operational costs

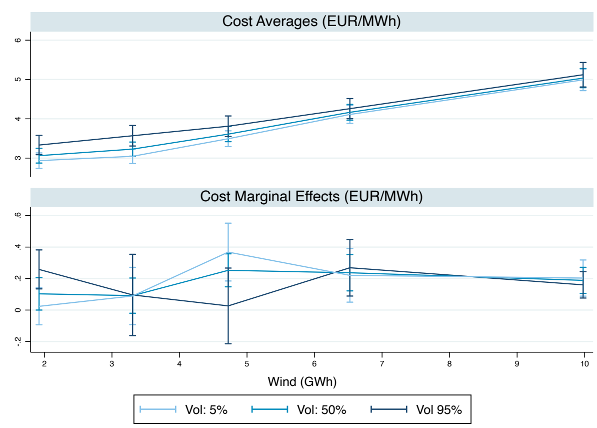
We further decompose the impacts of wind on operational costs across restrictions, frequency, and deviation costs. Figure 6a shows the average marginal effects of wind on the different components of operational costs using the definition in Equation (2). The impact on deviation costs is very limited 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 deviation management needs can increase on days with

[15] We obtain similar results with different time windows.

Figure 5: 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. Calculations based on marginal estimates from spline regressions with the controls of specification (4) in Table 2.

higher levels of wind generation. Therefore, it is not surprising that deviation costs are marginally increasing as wind penetration expands.

Figure 6a also shows that the marginal impact of wind tends to have the inverse U-shape pattern for each type of operational costs, with the exception of deviation costs. Why is it marginally easier to incorporate wind into the grid at high wind levels? To examine potential channels that explain this potentially counter-intuitive result, we rely on detailed bidding data for each of these markets at the power plant level. In the data, we observe both the offered bids as well as the accepted quantities.

We document two channels by which wind power is making *marginal* operational costs lower as it increases.[16] One possibility for this finding is that, at high levels of wind generation, more power plants are able and eager to participate in reliability markets to provide power, as they are otherwise unused, whereas at middle ranges of wind generation, the competition to provide reliability services might be less fierce. Indeed, we find that the offered quantity to increase production for restrictions, deviations and tertiary markets go up as wind increases, with the exception of secondary markets, which require plants to be operating (as shown in Figure A.5 in the Appendix). Another possibility is that there is an element of downward pressure in operational costs due to the downward pressure in the day-ahead market price. The opportunity cost for deviation and tertiary services is the day-ahead price. As more wind becomes available, the market price goes down and so do the equilibrium prices of these services (as shown in Figure A.6 in the Appendix). These two effects contribute to the inverse-U-shape that we observe. At high levels of wind, operational costs go up, but the marginal effect does not increase, and it can even go down.

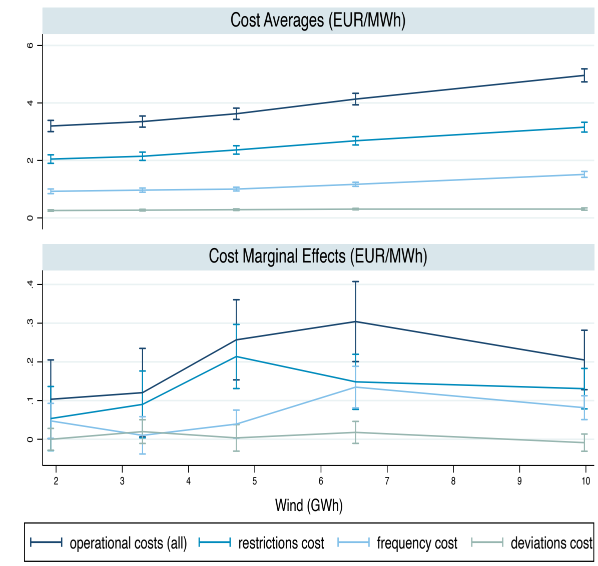
3.3 Market prices

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 wholesale electricity price, which includes capacity payments, reliability costs, and other operational costs pro-rated as a markup. These two prices are plotted in Figure 6b as day ahead price and wholesale price, respectively.

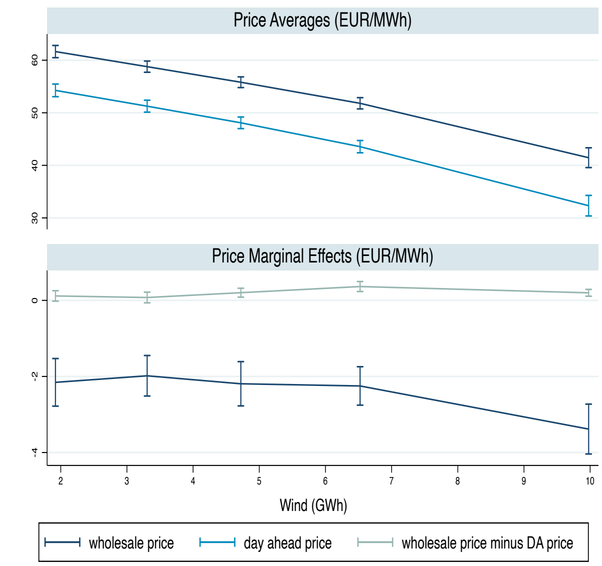
The downward sloping average prices and the negative margins in Figure 6b are clear indications of wind's tendency to reduce electricity prices, even after including operational costs. However, the difference between the day-ahead and wholesale price appears to marginally increase across the wind quintiles, confirming that more wind production has a positive effect on the operational cost

[16] One should keep in mind that total operational costs are increasing with wind power on average. Here we are focusing on marginal impacts.

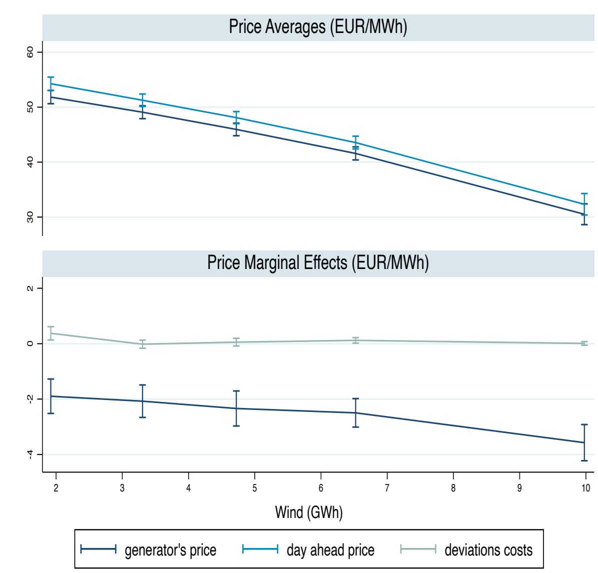
Figure 6: Impacts of Wind on Major Market Outcomes



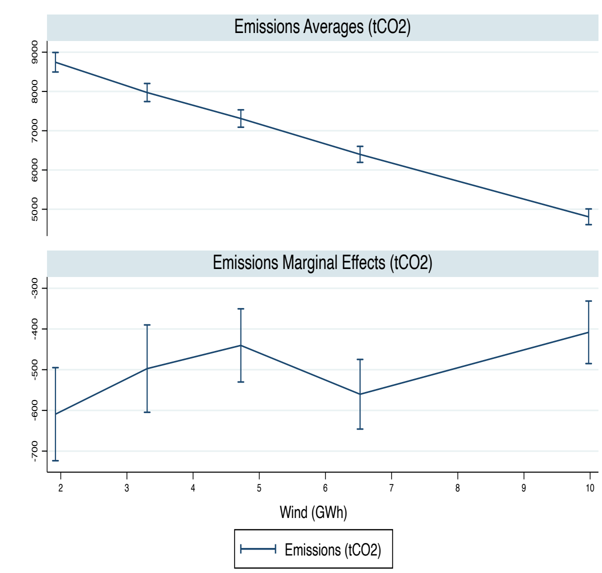
(a) Operational Costs



(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. Calculations based on marginal estimates from spline regressions with the controls of specification (4) in Table 2.

markup. This aligns with our earlier findings, which suggested that increasing wind production subsequently increases most operational cost components.

3.4 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.

One potential explanation is that, with low output, deviations are more likely, as variance is higher per unit of output. With a lot of wind, variance is higher but not in per unit of output terms. Another reason for lowered deviation costs is the availability of more idle thermal generators to compete in the deviations market during high wind hours, which should help reduce marginal operational costs (see Figure A.5). Due to equilibrium effects, high wind hours also put downward pressure in deviation prices via the low day-ahead energy prices (see Figures 6b and A.6), which is the opportunity cost of this service.

3.5 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).[17] However, at high levels of wind, carbon emissions in the Spanish Electricity Market decrease on average by only 66% of the margin seen at low wind levels, approximately -400 tCO_2 per additional GWh of wind. This decline can be explained by a decrease in the substitution of coal, wind curtailment as shown in Figure 2c, 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

[17]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.

could be larger.

4 Cost-benefit analysis of wind with intermittency

The estimates from Section 3 can be used to understand the marginal impacts of wind generation on economic welfare during our sample that accounts for the economic costs of wind intermittency. This enables us to do a marginal cost-benefit analysis for different levels of wind.

4.1 Components of the cost-benefit

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.[18] 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. We consider how results change if we ignore intermittency costs by assuming consumers don't need to pay increased operational charges.

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. We independently identify the impacts on non-wind producer surplus, and wind producer surplus.

For the price effect, which is a negative change in producer revenues, both non-wind and wind producers receive 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. We also assess the impact of these penalties by computing wind surplus when such effects are ignored.

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.[19] For wind producer surplus, the replacement effect requires us to factor in the levelized cost (LCOE)

[18] 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).

[19] 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.

of wind generation. As a measure of short-run surplus, we define wind producer surplus as wind revenue, which only includes the price and the subsidies received by wind producers. Due to the importance of the assumptions surrounding LCOE in our final analysis, we analyze the impact of capital costs separately.

Subsidies are a net transfer from consumers to producers.[20] 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 Figure 1. In the baseline results, we consider a 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.[21] 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.[22]

4.2 Results

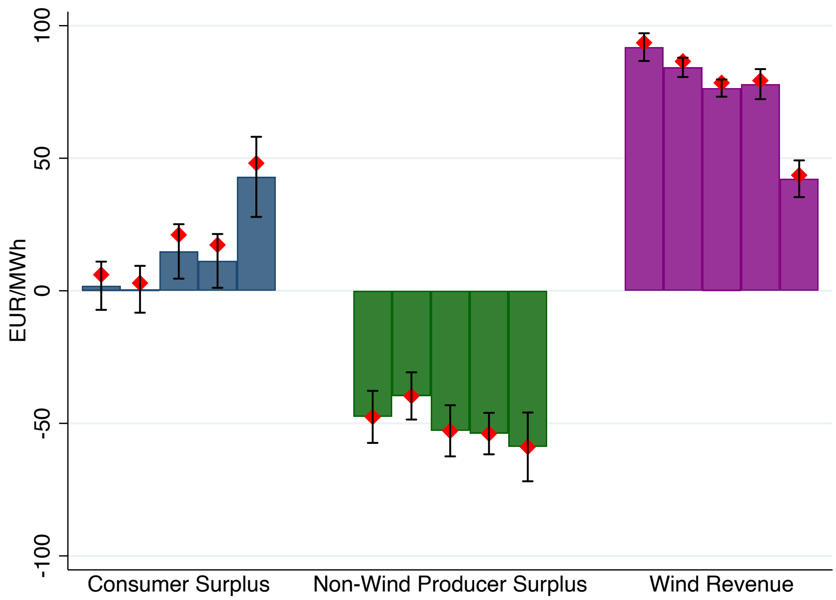
Figure 7 shows the results of our analysis for consumer surplus, non-wind producer surplus, and wind revenue at each wind quintile, with wind levels increasing from left to right within components. The impact of wind on consumer surplus (blue) is relatively small at low levels of wind, where the price effect is nearly equivalent to the cost of subsidies. However, at higher wind levels, a more dramatic decrease in electricity prices 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.

[20]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.

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

[22]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: Marginal Surplus 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. The red diamonds show surplus calculations when operational costs are ignored. Calculations based on marginal estimates from spline regressions with the controls of specification (4) in Table 2. All regressions include fixed effects of month-of-sample interacted with hour.

The red diamonds in Figure 7 are estimates for how consumer, traditional producer, and wind farm surplus margins would differ if the marginal impact of wind on operational costs were 0 EUR/MWh. To do this, we re-estimate the regressions utilizing day-ahead prices rather than wholesale prices[23] or day-ahead plus deviation costs for consumer surplus and wind farm revenues, respectively.[24] As one can see, ignoring intermittency has limited impact on the different surplus categories. In the no operational costs counterfactual, wind farms would benefit slightly from not facing deviation penalties, while consumers surplus would be more improved, though not significantly. Importantly, these effects do not countervail the positive gains to these two sets of stakeholders.

To analyze the overall cost-benefit, 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 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.[25]

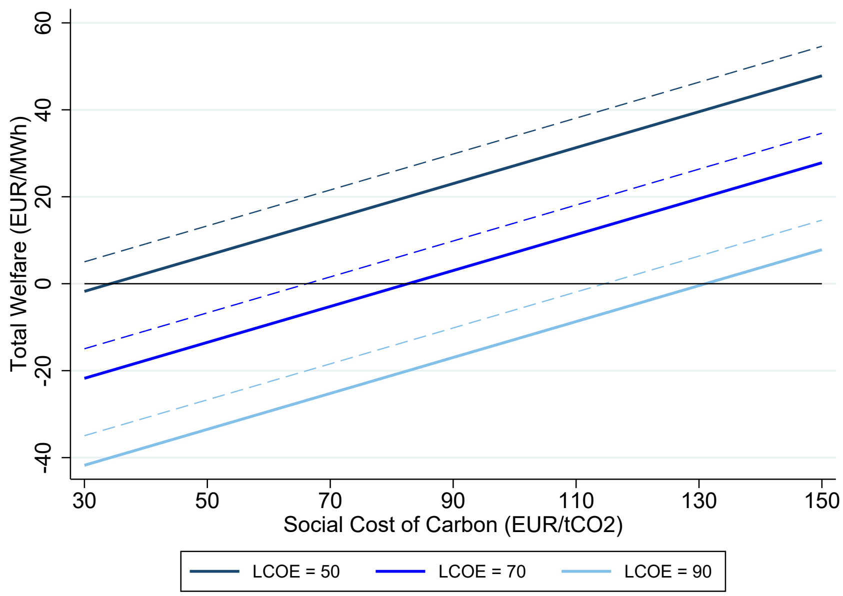
Similar to the red diamonds in Figure 7, the dashed lines in Figure 8 demonstrate how the cost-benefit lines would shift in the counterfactual scenario in which the marginal impact of wind on operational costs were equal to 0 EUR/MWh. The rise in operational costs due to wind causes the marginal benefit curves to shift downwards by 5-10 EUR/MWh. The political implication of this shift is that a higher social cost of carbon (roughly 15 EUR/tCO2 higher) is required for wind expansion to be welfare positive at any given LCOE.

[23] We assume that other elements of the markup between wholesale prices and day-ahead prices, aside from operational costs, are independent of wind generation.

[24] Given our simplifying assumptions, traditional producer surplus is not impacted by operational costs, and thus the red diamonds for this category is intentionally unchanged from the bar chart.

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

Figure 8: Marginal Investment Cost-Benefit Analysis



Notes: This figure illustrates the cost-benefit of increases in 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. The dashed lines show the same calculation when operational costs are ignored. Calculations based on marginal estimates from spline regressions with the controls of specification (4) in Table 2. All regressions include fixed effects of month-of-sample interacted with hour.

5 Conclusion

We analyze the benefits and costs of wind production in the context of the Spanish Electricity Market. We exploit the exogeneity of wind forecasts to show the marginal effect of wind on several relevant market outcomes. 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. 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 most levels of wind, both wind revenue and consumer surplus are positively impacted by the inclusion of wind power and its corresponding subsidies. Under reasonable levels for LCOE and the social cost of carbon, the change in total welfare due to wind expansion in Spain is positive. These gains make early investments in wind power cost effective for typical 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.[26] Finally, active modifications to the market design can improve wind participation in organized electricity markets and reduce the operational costs of accommodating these sources of energy into the grid.

[26] 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).

References

Abrell, J., M. Kosch, and S. Rausch (2019, jan). Carbon abatement with renewables: Evaluating wind and solar subsidies in Germany and Spain. *Journal of Public Economics 169*, 172–202.

Aldy, J., T. Gerarden, and R. Sweeney (2023). Investment versus Output Subsidies: Implications of Alternative Incentives for Wind Energy. *Journal of the Association of Environmental and Resource Economists 10*(4), 981–1018.

Batalla-Bejerano, J. and E. Trujillo-Baute (2016, 7). Impacts of intermittent renewable generation on electricity system costs. *Energy Policy 94*, 411–420.

Borenstein, S. (2012). The Private and Public Economics of Renewable Electricity Generation. *Journal of Economic Perspectives 26*(1), 67 – 92.

Bueb, J., B. Le Hir, B. Mesqui, A. Pommeret, G. de Margerie, M. Salin, E. Quinet, O. de Broca, S. Chasseloup, M. Combaud, D. Bureau, C. Gollier, A. Quinet, A. Millot, N. Maizi, S. Cail, Q. Bchini, B. Boitier, A. Fougeyrollas, G. Koleda, P. Le Mouel, P. Zagame, G. Callonnec, R. Cance, A. Saussay, P. Criqui, F. Dassa, J.-M. Trochet, S. De Cara, L. Bamiere, and P.-A. Jayet (2019, feb). The Value for Climate Action. A shadow price of carbon for evaluation of investments and public policies. Report by the Commission chaired by Alain Quinet.

Bushnell, J. and K. Novan (2021). Setting with the sun: The impacts of renewable energy on conventional generation. *Journal of the Association of Environmental and Resource Economists 8*(4), 759–796.

Callaway, D., M. Fowlie, and G. McCormick (2018). Location, location, location: The variable value of renewable energy and demand-side efficiency resources. *Journal of the Association of Environmental and Resource Economists 5*(1), 39–75.

Ciarreta, A., C. Pizarro-Irizar, and A. Zarraga (2020, 4). Renewable energy regulation and structural breaks: An empirical analysis of Spanish electricity price volatility. *Energy Economics 88*.

Comisión Nacional de la Energía (2018). Información mensual de estadísticas sobre las ventas de régimen especial. Contiene información hasta marzo de 2018. https://www.cnmc.es/estadistica/informacion-mensual-de-estadisticas-sobre-las-ventas-de-regimen-especial-contiene-19. Accessed: 2021-07-14.

Cullen, J. (2013, November). Measuring the environmental benefits of wind-generated electricity. *American Economic Journal: Economic Policy 5*(4), 107–33.

Dorsey-Palmateer, R. (2019, 4). Effects of wind power intermittency on generation and emissions. *The Electricity Journal 32*(3), 25–30.

Eising, M., H. Hobbie, and D. Mst (2020, 1). Future wind and solar power market values in Germany Evidence of spatial and technological dependencies? *Energy Economics 86*.

Fabra, N. and Imelda (2021, May). Market Power and Price Exposure: Learning from Changes in Renewables Regulation. (EPRG2117).

Fabra, N., D. Rapson, M. Reguant, and J. Wang (2021, may). Estimating the Elasticity to Real-Time Pricing: Evidence from the Spanish Electricity Market. *AEA Papers and Proceedings 111*, 425–29.

Fabra, N. and M. Reguant (2014). Pass-through of emissions costs in electricity markets. *American Economic Review 104*(9).

Gelabert, L., X. Labandeira, and P. Linares (2011). An ex-post analysis of the effect of renewables and cogeneration on spanish electricity prices. *Energy Economics 33*, S59 – S65. Supplemental Issue: Fourth Atlantic Workshop in Energy and Environmental Economics.

Gowrisankaran, G., S. S. Reynolds, and M. Samano (2016, August). Intermittency and the value of renewable energy. *Journal of Political Economy*.

Gross, R. and P. Heptonstall (2008). The costs and impacts of intermittency: An ongoing debate: East is east, and west is west, and never the twain shall meet. *Energy Policy 36*(10), 4005 – 4007.

Gutierrez-Martin, F., R. D. Silva-Álvarez, and P. Montoro-Pintado (2013, 11). Effects of wind intermittency on reduction of CO2 emissions: The case of the Spanish power system. *Energy 61*, 108–117.

Hirth, L. (2013, 2). The market value of variable renewables, The effect of solar wind power variability on their relative price. *Energy Economics 38*, 218–236.

Hirth, L. (2015). The Optimal Share of Variable Renewables: How the Variability of Wind and Solar Power affects their Welfare-optimal Deployment. *The Energy Journal 36*.

Hirth, L. (2016, 8). The benefits of flexibility: The value of wind energy with hydropower. *Applied Energy 181*, 2010–223.

Hirth, L., F. Ueckerdt, and O. Edenhofer (2015). Integration costs revisited an economic framework for wind and solar variability. *Renewable Energy 74*, 925 – 939.

Ito, K. and M. Reguant (2016). Sequential markets, market power, and arbitrage. *American Economic Review 106*(7), 1921–57.

Johnston, S. (2019). Nonrefundable tax credits versus grants: The impact of subsidy form on the effectiveness of subsidies for renewable energy. *Journal of the Association of Environmental and Resource Economists 6*(3), 433–460.

Joskow, P. L. (2011a). Comparing the Costs of Intermittent and Dispatchable Electricity Generating Technologies. *American Economic Review 101*(3), 238 – 41.

Joskow, P. L. (2011b, May). Comparing the costs of intermittent and dispatchable electricity generating technologies. *American Economic Review 101*(3), 238–41.

Joskow, P. L. (2019). Challenges for wholesale electricity markets with intermittent renewable generation at scale: The US experience. *Oxford Review of Economic Policy*.

Kaffine, D. T., B. J. McBee, and S. J. Ericson (2020). Intermittency and co2 reductions from wind energy. *The Energy Journal 41*(5).

Kaffine, D. T., B. J. McBee, and J. Lieskovsky (2013). Emissions savings from wind power generation in texas. *Energy Journal 34*(1), 155 – 175.

Ketterer, J. (2014, 5). The impact of wind power generation on the electricity price in Germany. *Energy Economics 44*, 270–280.

Liski, M. and I. Vehvilinen (2020). Gone with the Wind? An Empirical Analysis of the Equilibrium Impact of Renewable Energy. *Journal of the Association of Environmental and Resource Economists 7*(5), 873–900.

Maciejowska, K. (2020, 10). Assessing the impact of renewable energy sources on the electricity price level and variability A quantile regression approach. *Energy Economics 85*.

Mastropietro, P. (2019, oct). Who should pay to support renewable electricity? Exploring regressive impacts, energy poverty and tariff equity. *Energy Research & Social Science 56*, 101222.

Milligan, M., E. Ela, B.-M. Hodge, B. Kirby, D. Lew, C. Clark, J. DeCesaro, and K. Lynn (2011). Integration of variable generation, cost-causation, and integration costs. *National Renewable Energy Laboratory (NREL)*.

Mwampashi, M. M., C. S. Nikitopoulos, O. Konstandatos, and A. Rai (2021). Wind generation and the dynamics of electricity prices in australia. *Energy Economics 103*.

Newell, R., W. Pizer, and B. Prest (2022). A Discounting Rule for the Social Cost of Carbon. *Journal of the Association of Environmental and Resource Economists 9*(5), 1017–1046.

Novan, K. (2015, August). Valuing the wind: Renewable energy policies and air pollution avoided. *American Economic Journal: Economic Policy 7*(3), 291–326.

Pena, J. I., R. Rodrguez, and S. Mayoral (2022). Cannibalization, depredation, and market remuneration of power plants. *Energy Policy 167*.

Prol, J. L., K. W. Steininger, and D. Zilberman (2020). The cannibalization effect of wind and solar in the California wholesale electricity market. *Energy Economics 85*.

Reguant, M. (2019, mar). The Efficiency and Sectoral Distributional Impacts of Large-Scale Renewable Energy Policies. *Journal of the Association of Environmental and Resource Economists 6*(S1), S129–S168.

Sexton, S., J. Kirkpatrick, R. Harris, and N. Muller (2021, 5). Heterogeneous Solar Capacity Bene ts, Appropriability, and the Costs of Suboptimal Siting. *Journal of the Association of Environmental and Resource Economists*.

Siler-Evans, K., I. L. Azevedo, and M. G. Morgan (2012). Marginal emissions factors for the u.s. electricity system. *Environmental Science & Technology 46*(9), 4742–4748.

Swider, D. J. and C. Weber (2007). The costs of wind's intermittency in germany: application of a stochastic electricity market model. *European Transactions on Electrical Power 17*(2), 151–172.

Woo, C., I. Horowitz, J. Moore, and A. Pacheco (2011, 5). The impact of wind generation on the electricity spot-market price level and variance: The Texas experience. *Energy Policy 39*, 3939 – 3944.

A Additional Tables and Figures

Table A.1: Regulation changes

Regulation	Summary	Notes
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.	See Fabra and Imelda (2021) for a treatment of this change back from FiT.
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

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.

Table A.3: Impact of wind vs. forecasted wind

	(1)	(2)	(3)	(4)
VARIABLES	Wind Forecast	Wind	IV Forecast	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

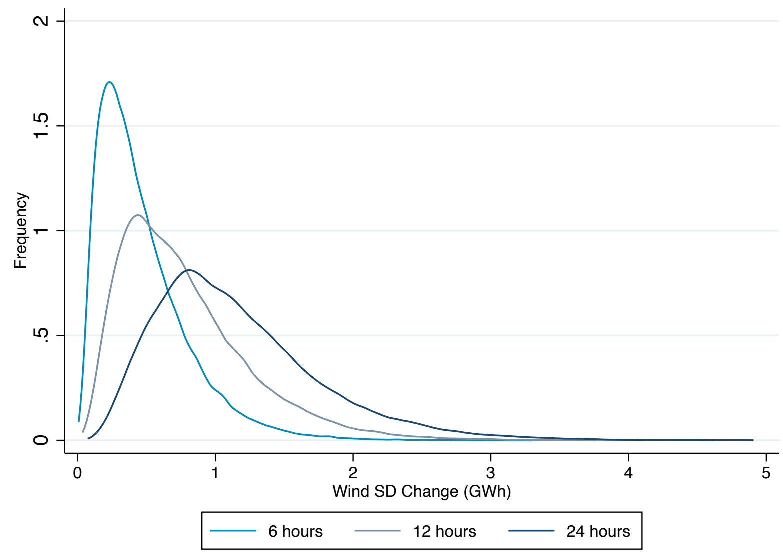
Notes: Standard errors clustered at the month of sample. All regressions include demand forecast, natural gas prices, temperature, temperature squared, dew point, and solar production as controls.

Table A.4: Daily marginal impacts to operational costs

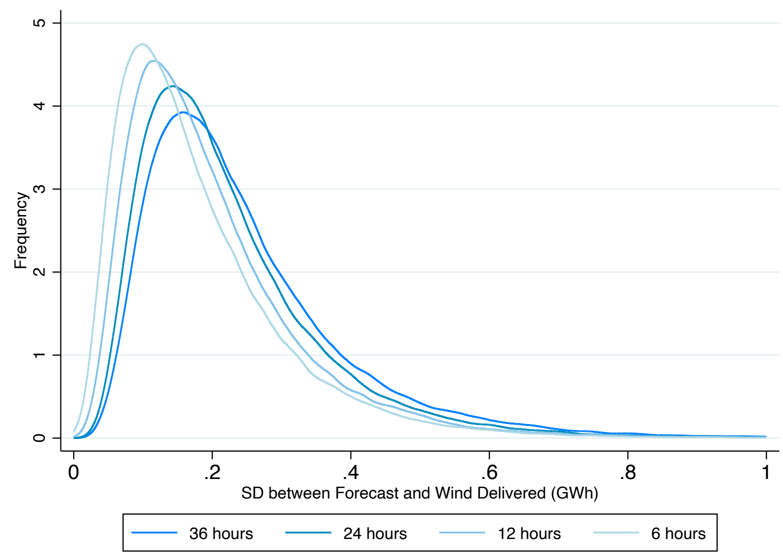
VARIABLES	(1)	(2)	(3)	(4)
Forecasted wind (GWh)	6.131	6.128	6.282	6.152
	(0.457)	(0.457)	(0.457)	(0.476)
Forecasted demand (GWh)	0.0339	0.00405	-0.112	-0.0955
	(0.543)	(0.531)	(0.528)	(0.533)
Solar production (GWh)	8.406	8.703	8.451	6.104
	(5.150)	(5.098)	(5.330)	(6.439)
NG price (EUR/MWh)		11.29	5.375	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.

Figure A.1: Distribution of wind intermittency



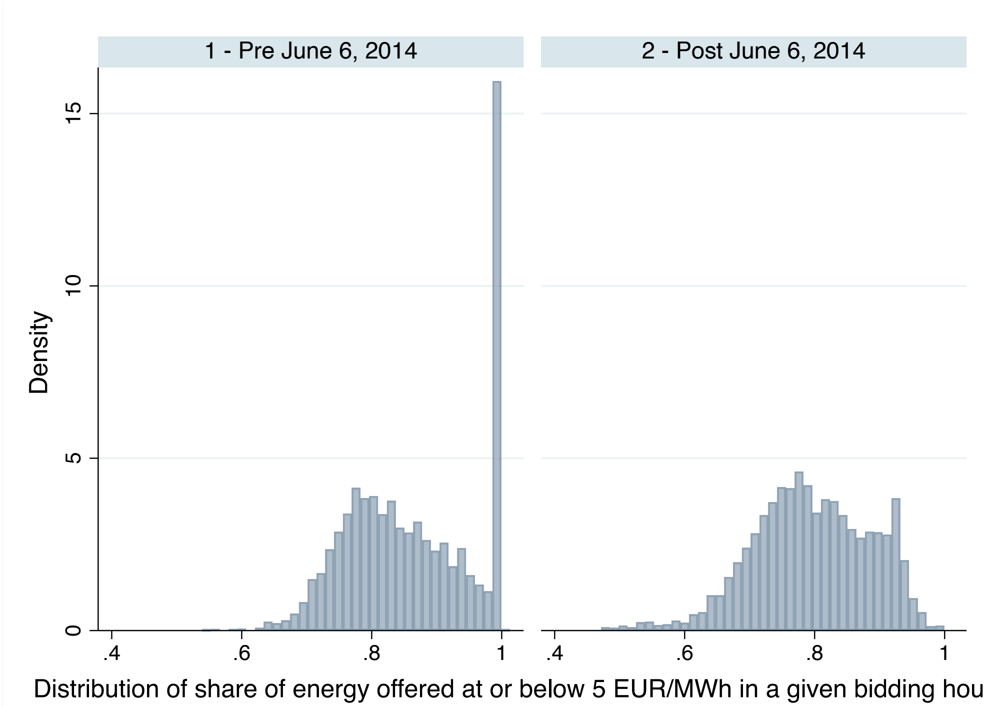
(a) Volatility



(b) Uncertainty

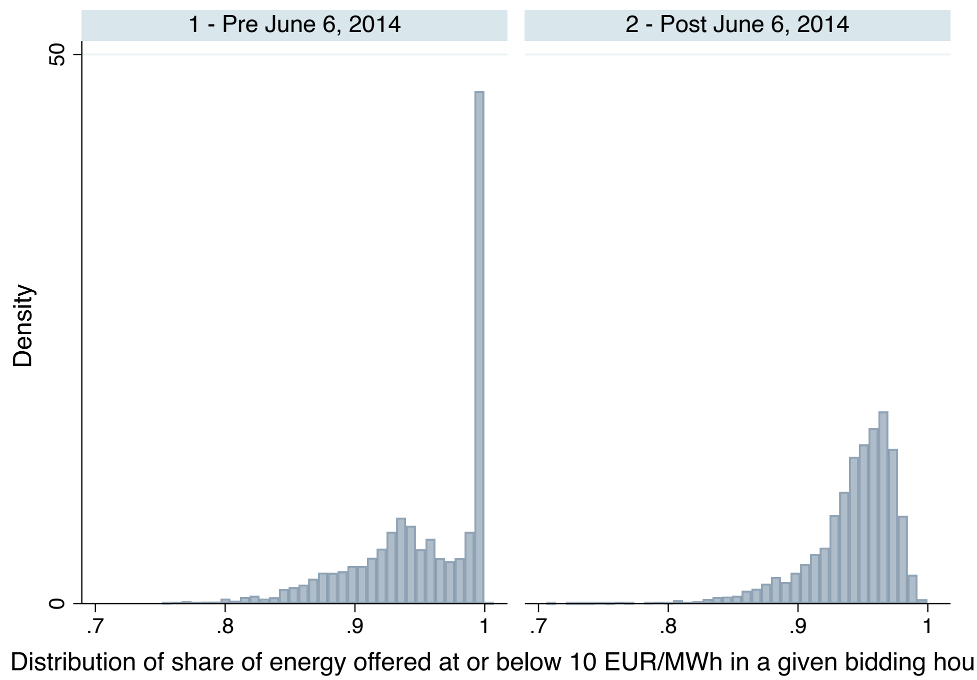
Notes: This figure shows two measures of intermittency: volatility and uncertainty. Volatility is defined as the standard deviation of changes in wind production during a certain length of time. We have computed volatility for 6, 12, and 24 hours output differences. Uncertainty is defined as the standard 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: 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.3: 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.

Figure A.4: Marginal quintile impact by year

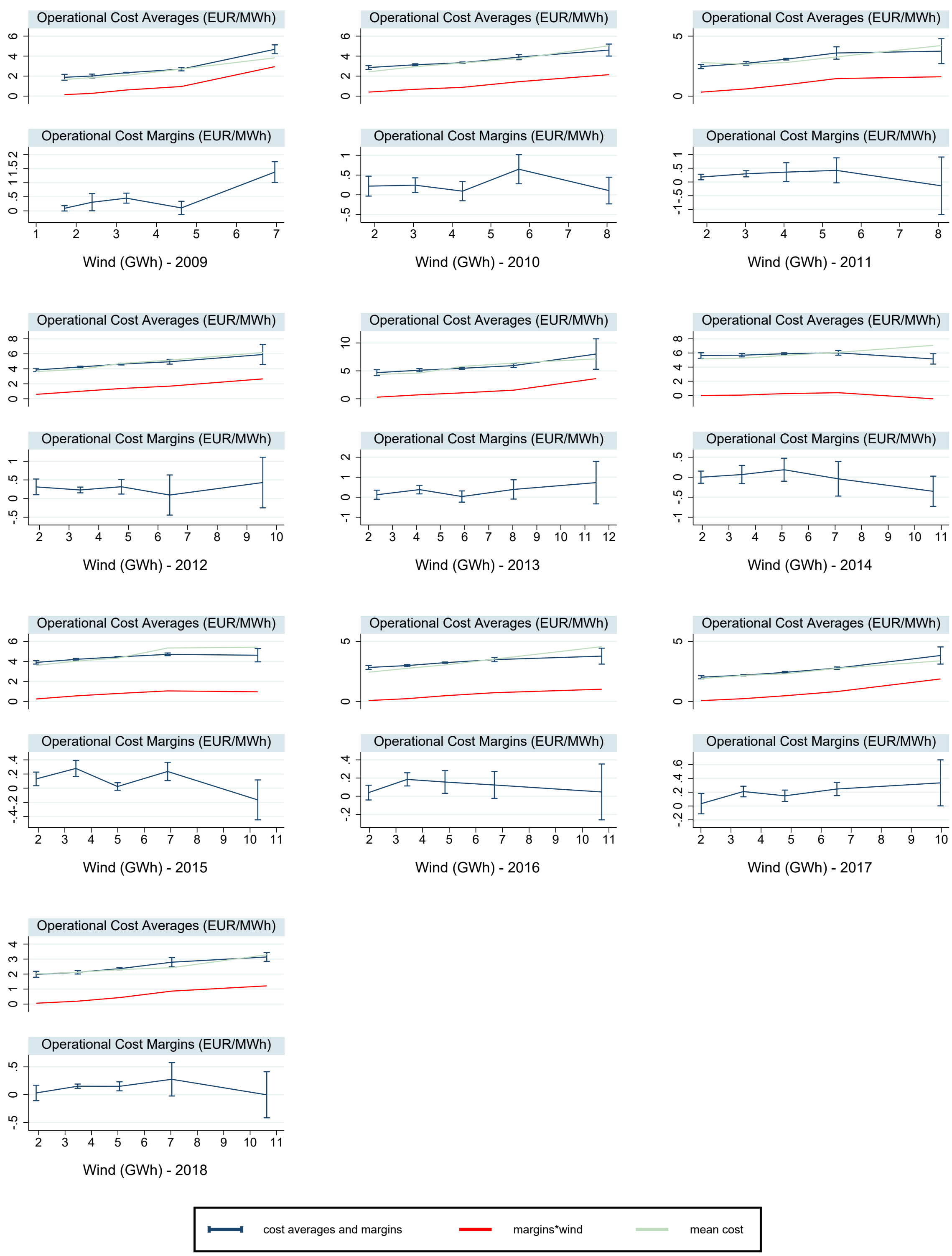
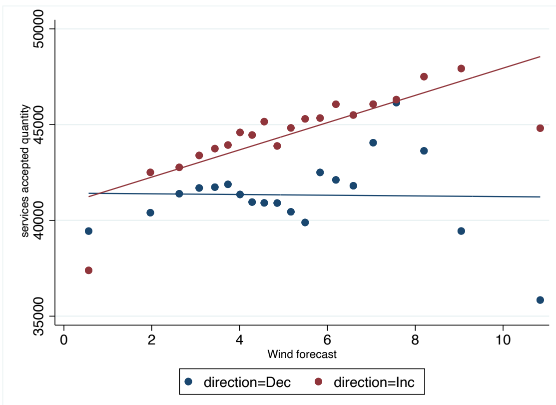
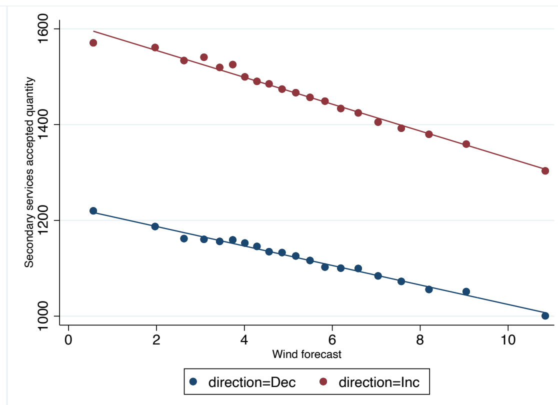


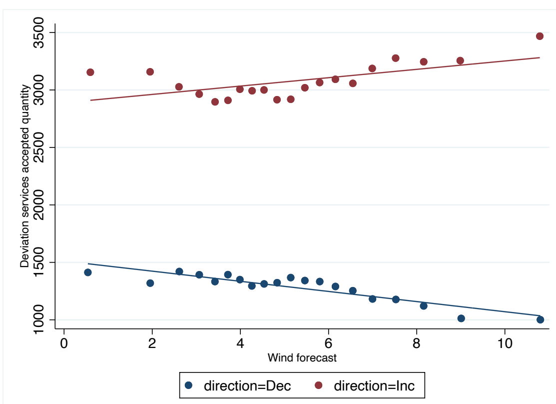
Figure A.5: Offered quantity in reliability markets by wind production forecast



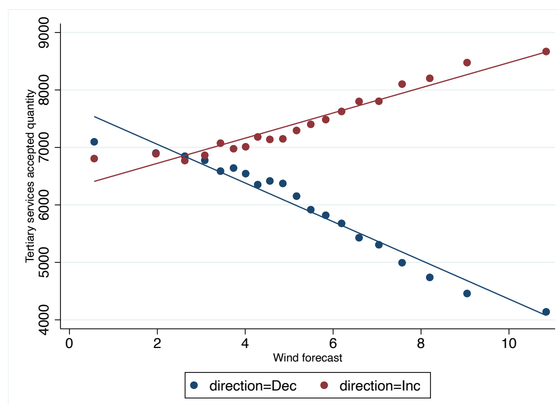
(a) Restrictions market



(b) Secondary market

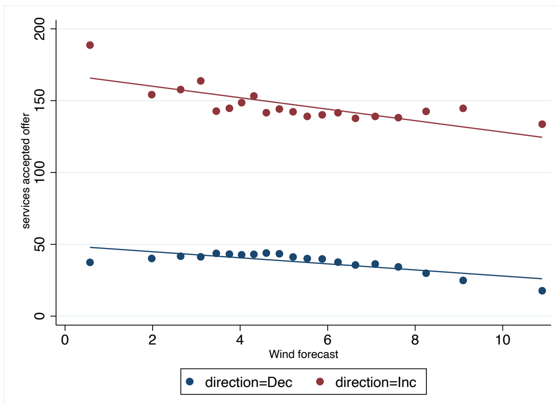


(c) Deviation Market

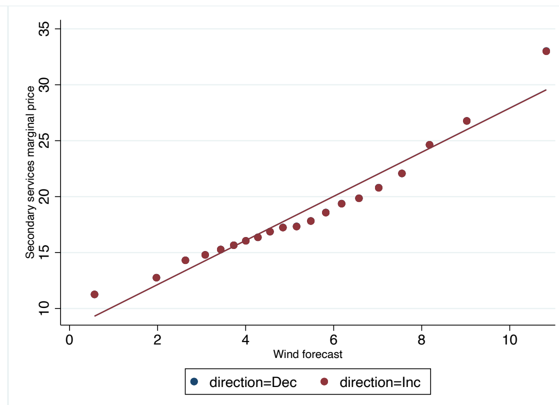


(d) Tertiary market

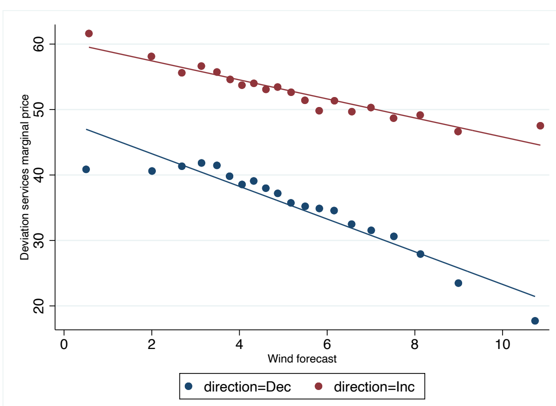
Figure A.6: Accepted prices in reliability markets by wind production forecast



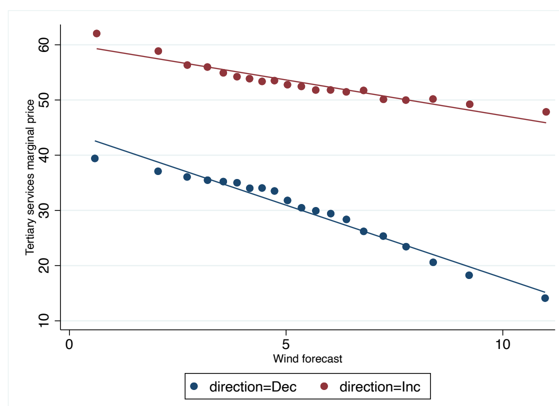
(a) Restrictions market



(b) Secondary market



(c) Deviation Market



(d) Tertiary market