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Wind, Storage, Interconnection and the Cost of Electricity Generation

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Keywords: Wind Generation, Constraints, Storage, Interconnection, Subsidies

JEL Classification: L94, Q42

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Wind, storage, interconnection and the cost of electricity generation

Valeria Di Cosmo*and Laura Malaguzzi Valeri†

Abstract

We evaluate how increasing wind generation affects wholesale electricity prices, balancing payments and the cost of subsidies using the Irish Single Electricity Market (SEM) as a test system, with hourly data from 1 January 2008 to 28 August 2012. We model the spot market using a system of seemingly unrelated regressions (SUR) where the regressions are the 24 hours of the day. Wind has a negative impact on the system marginal price, with every MWh increase in wind generation (equal to about 0.2% of the average wind generation in our sample) leading to a decrease of the system marginal price of €0.018/MWh, or about 0.3% of its average value. We use time series models to analyse the balancing market and show that wind generation increases balancing payments, as do the forecast errors of demand and wind. Every MWh of additional wind generation is associated with an increase in constraint payments of €3.2, or about 0.01%. Lack of storage increases the impact of wind on balancing payments whereas the lack of interconnection has no effect. Overall, wind decreases costs through its effect on the electricity price more than it increases constraint payments, even when storage is on outage. The effect of wind remains positive after including the cost of subsidies given to wind generation.

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1 Introduction

As the share of renewable electricity increases worldwide, its impact on electricity system prices and costs will increase. The direct effect of renewables on wholesale prices (the merit order effect) is typically negative as they provide generation at very low or zero marginal cost and displace more costly generation. Renewables can also decrease prices indirectly by lowering market power in systems where generators bid strategically, as highlighted by Browne et al. (2015) and Ben-Moshe and Rubin (2015). At the same time, integrating generation that is intermittent and difficult to predict has costs. Plants with predictable generation have to be ready for back up if there is a sudden drop in wind or solar production (Currie et al., 2006) and renewables do not easily provide frequency and voltage control (Romero Martinez and Hughes, 2015; EirGrid and SONI, 2014).

This paper first contributes to the literature evaluating the effect of wind on spot prices. Second, it adds to the limited literature analysing the effect of wind on balancing costs, defined as the costs associated with balancing electricity supply with demand in real time. Third, it evaluates the impact of renewable support on the cost of electricity to consumers. Finally, it addresses the impact of storage and interconnection on the effect of wind, taking advantage of a natural experiment.

The literature on the effect of renewables on electricity prices is vast and growing. Earlier papers relied on simulations (see e.g. Traber and Kemfert, 2011; Holttinen et al., 2011; Garcia-Gonzalez et al., 2008; Rehman et al., 2015). As renewable penetration has grown, researchers have started estimating the effect of renewables using historical data. For Germany and Austria, see Würzburg et al. (2013) and Cludius et al. (2014); for Spain, Gelabert et al. (2011) and Gil et al. (2012); for Australia, Forrest and MacGill (2013). These studies use econometric approaches and find a negative effect of renewables on electricity prices but do not analyse balancing markets.

Batalla-Bejerano and Trujillo-Baute (2016) find a positive and significant impact of renewable generation (solar and wind) on balancing costs for Spain. On the other hand, Hirth and Ziegenhagen (2015) and Gianfreda et al. (2016) analyse the German and Italian market respectively and find that increasing renewable generation did not increase balancing costs in these markets, possibly because of well-functioning intra-day markets although these exist in Spain as well (Chaves-Ávila and Fernandes, 2015).

Subsidies can significantly impact final consumers' bills, making wind generation on net costly to consumers, as highlighted by Ciarreta et al. (2014) for the Spanish market and by Munksgaard and Morthorst (2008) for the Danish market. Neither of these studies include balancing costs in their analysis.

We study the Irish Single Electricity Market (SEM), encompassing both the Republic of Ireland and Northern Ireland, and use hourly data from 1 January 2008 to 28 August 2012. Several studies have examined some aspects of the SEM. Sustainable Energy Authority of Ireland and EirGrid (2011) use simulations to assess the impact of wind generation on SEM wholesale prices in 2011 and find that wind decreases prices more than the cost of subsidies. They do not consider balancing markets. Swinand and O'Mahoney (2015) examine the effect of wind on spot and balancing markets for the 2008-2012 period, but only for the Republic of Ireland and do not measure the cost of subsidies.

The dataset for the island of Ireland is particularly well-suited to our analysis. First, extensive data on the system are available from the beginning of the SEM in November 2007. The compulsory nature of the SEM means that every generator with a capacity larger than 10MW has to offer electricity on the market. Similarly, all buyers have to buy from the pool. We are therefore able to base our analysis on complete system data, which is not possible for jurisdictions where generators and consumers engage in bilateral contracts outside of the main market. Second, the island has limited interconnection with other systems allowing us to identify the effect of wind more easily. Third, it has experienced a large increase in wind capacity, more than doubling from about 900MW (or 10% of total capacity) at the end of 2007 to almost 2100MW at the end of August 2012 (or 19% of total capacity).

Finally, unexpected and persistent outages at the main storage plant in the SEM and at the interconnector between the SEM and Great Britain provide natural experiments for the evaluation of the effect of storage and interconnection on system prices both directly and via their interaction with wind generation.

As expected, we find a negative correlation between the system marginal price (SMP) and wind generation. When large-scale storage is not available the marginal effect of wind on the spot price increases at night. When interconnection is not available the effect of wind decreases for a few hours during the day. On the other hand wind generation is positively correlated with the constraint payments provided to generators, our measure of balancing costs. The effect of wind on constraint payments increases when storage is not available.

Our results show that overall the effect of wind on system prices is positive, as its dampening effect on marginal prices is stronger than the sum of its effect on constraint payments and the costs of subsidies given to wind generators. When storage is significantly reduced, the effect of wind on constraint payments more than doubles, but on net it still reduces costs. The existence (or absence) of interconnection has a much weaker effect on wind's propensity to affect system costs.

The rest of the paper is organised as follows. Section 2 depicts the SEM in more detail. Section 3 describes the data. Section 4 explains our methodology and describes the estimation of the effect of wind on the system marginal price. Section 5 presents the results for constraint payments. Section 6 describes the subsidies accorded to wind and estimates their size while Section 7 concludes.

2 The SEM

The Irish electricity market encompasses the electricity systems of both the Republic of Ireland and Northern Ireland, making it a cross-jurisdiction, cross-currency system.

The contribution of renewable electricity to overall electricity demand was about 20% in 2013 for the Republic of Ireland (Dineen et al., 2015) and 19% for Northern Ireland in 2014 (Department of Enterprise Trade and Investment, 2015). Renewable penetration in electricity generation is expected to reach 40% by 2020 if the two jurisdictions are to meet their renewable energy targets under the European Directive (2009/28/EC) (DETI, 2010; DCENR, 2012).[1] The electricity mix in the SEM changed between 2008 to 2012. Installed wind capacity increased from 12.5% in 2008 to 18.5% of total generation capacity in 2012 (excluding interconnection capacity). Combined-Cycle Gas Turbine generators (CCGTs) increased their share of capacity from 32.8% in 2008 to 37.7% in 2012. Capacity of open-cycle gas turbines, natural gas combustion turbines, distillate and oil was 32.6% of the total in 2008, decreasing to 24.7% in 2012. Coal and peat were 14.5% of the total capacity installed in 2012, down from 16.9% in 2008. Hydro remained constant during the period at 3% of total capacity.[2]

The SEM is a compulsory pool system for all plants with a capacity of at least 10MW. Plants bid in the day-ahead market and generate on the basis of the merit order: plants with lower bids are called to generate ahead of more expensive plants until total generation equals total demand. Each plant's bid reflects its short run marginal costs and includes the cost of fuel and carbon dioxide emission permits needed to generate a megawatthour (MWh) of electricity, in addition to operation costs. Generators submit up to 10 price-quantity pairs that apply to all 48 half hours during a 24-hour period, but can change every 24 hours. The System Marginal Price (SMP) reflects the bid of the marginal plant, or the cost of generating the most expensive unit of electricity needed to meet demand. There are no intra-day markets. Any difference between the day-ahead and the real time dispatch is dealt with through the constraint payment regime, as explained in detail in section 5.

The regulation authority monitors the market through the market monitoring unit. Power plants are required to bid their short run marginal cost in line with the bidding code of practice available from the regulator's website (`http:www.semcommittee.com`). As an additional check of market power there is a system of future contracts in the form of contracts for differences (CfD). Existing evidence suggests that this regulation is successful, leading to limited market power (Gorecki, 2013; Market Monitoring Unit, 2009; Walsh et al., 2016).

In addition to the short-run payments, power plants also receive capacity payments, designed to cover additional capital costs.

It's useful to highlight some of the characteristics of the SEM SMP:

- It has never been censored from above, due to a high upper bound (at €1000/MWh) and firms' bidding behavior being regulated.

[1]The Directive is available at (`http://eur-lex.europa.eu/LexUriServ/LexUriServ.do?uri=OJ:L:2009:140:0016:0062:en:PDF`.

[2]Information elaborated from SONI and EirGrid reports, including SONI (2008), EirGrid (2008, 2009); EirGrid and SONI (2010, 2011, 2013b).

- There are no negative prices, despite negative prices being theoretically possible. At the moment wind companies are price takers and do not therefore bid a price in the system. Since 2011 they have priority dispatch, in line with EU rules.[3]

- Electricity consumers do not bid directly in the market, except for a few virtual plants that can bid in decreases of demand. The SMP is calculated on the basis of the supply curve (based on the merit order of day-ahead bids from generators) and actual demand in every period. The SMP is finalised ex post, after actual levels of demand are verified.

- All bidders and all consumers (represented by suppliers) obtain and pay the same uniform wholesale price of electricity in every period.

- In the short run electricity demand is not elastic to price, given the limited bidding on the demand side.

- During our period of analysis the Transmission System Operators (TSO) curtailed wind if it exceeded 50% of demand at any given time, to ensure system stability, in particular voltage and frequency control.[4]

Bidding rules in the SEM have been modified and clarified over time. Table 1 summarises the main changes to the Bidding Code of Practice. In 2010 the government tried to recover windfall gains to thermal generators that came from the free allocation of carbon dioxide permits. It instituted a 'carbon levy' and stated that it could not be included in bids and therefore passed on to consumers. In 2012 the Supreme Court ruled that the carbon levy could be passed onto consumers, causing its repeal within a few months. During those months generators were allowed to include the cost of carbon twice in their bids, once for the European Trading System and once for the carbon levy.

We highlight these changes since they may have systematically affected bidding behaviour and therefore market prices although, as discussed in Section 3, we find no structural breaks associated with these dates. The SEM operated from 2007 until 2016. By 2017 it needs to comply with the European Target Model (SEM, 2014).

[3]The SEM has always included wind generation when available since it dispatches plants based on their marginal cost SEM (2011). Priority dispatch of renewables is addressed in article 16 of EU Directive 2009/28/EC and was transposed into law in the Republic of Ireland by Statutory Instrument 147 of 2011 and in Northern Ireland by Statutory Rule 385 of 2012.

[4]Since our study period, the system has been accommodating more wind. During the 2014-2015 winter, wind has generated up to 63% of instantaneous demand, see: `http://www.eirgrid.com/media/All-Island_Wind_and_Fuel_Mix_Report_December_2014(2).pdf`.

Table 1: SEM: changes in Bidding Code of Practice, 2007-2012

Date	Decision	Notes	Reference
Nov. 2007	SEM starts		
12 Jun. 2008	How to bid	Start-up costs should include cycling; incremental costs should not. Bids can deviate from spot price for 'good reason' (e.g. use it or lose it).	SEM-08-069
18 Dec. 2008	How to include Transmission and Combined Loss Adj. Factor (TLAF and CLAF) into bids	Generators to include loss factors in price, no-load and start-up costs.	SEM-11-010; SEM-11-010a
10 Feb. 2009	Start-up costs	Should not depend on plant status (off versus on).	SEM-09-014
8 Oct. 2010	Exclusion of carbon levy costs from bids	Gov. tries to recover windfall gains from free allocation of CO_2 permits.	Modification of Electricity Act
23 Feb. 2012	Supreme Court ruling on carbon levy costs	Generators can include levy costs in bids.	
1 Mar. 2012	Regulators allow carbon levy costs in bids		SEM-12-015
May 2012	Modification of Electricity Act overturned	Carbon levy costs eliminated from bids.	

3 Data

We build a dataset of hourly information for electricity generation, demand, plant availability and daily data on fuel and carbon costs from 1 January 2008 to 28 August 2012.

Most of the data on the SEM is downloaded directly from the system operator, SEMO, with the exception of wind generation and electricity demand. Quarter-hour wind generation for the Republic of Ireland comes from EirGrid and half-hour wind generation for Northern Ireland comes from SONI, the system operators of the Republic of Ireland and Northern Ireland respectively. These sources include both wind farms registered with the SEM and generation estimates for smaller wind farms not registered with the SEM. Unregistered wind accounts for 20% to 25% of total wind generation, during the 2008-2012 period.[5] We aggregate the series to hourly levels. We also take demand information from EirGrid and SONI to obtain all-island demand, gross of transmission and distribution losses. We think it is a better measure of demand than the load variable provided by SEMO. The SEMO load variable is net of imports and exports to the system, nets demand by the amount of electricity produced by wind that is not registered directly with SEMO and includes electricity used by pumped storage.

We also measure wind and demand forecast errors, as they affect constraint payments. We define the forecast errors as actual levels minus the day-ahead expected value. The

[5]We obtain this estimate by comparing wind generation of the wind farms registered with SEMO with total wind generation estimated by EirGrid and SONI.

day-ahead expected value is only available from SEMO and therefore refers to wind farms registered with SEMO and the SEMO definition of load. This is not a big problem for the wind forecast error, as the correlation between the wind reported in SEMO and the series built from EirGrid and SONI data is 0.996. The day-ahead information for wind is available from 6 a.m. on 1 January 2009, leading to 8766 fewer observations. Over the years there are another approximately 200 observations missing, for a final 31,843 observations. The day-ahead information on load is available from 1 November 2009 at 6 a.m., leading to 16,036 fewer observations for the demand forecast error. The correlation between SEMO's load variable and the demand built using EirGrid and SONI information is 0.986 from 1 November 2009 to 28 August 2012. While still high, the differences could be systematic and influence parameter estimates (see Di Cosmo and Malaguzzi Valeri, 2014). To limit this concern we include forecast errors (i.e. differences between actual and forecast levels) rather than forecasts in levels.

For all series we have to decide how to address the time changes associated with Daylight Saving Time. For the spring change we set the values for 1 a.m. equal to their level the prior hour. For the autumn, we eliminate the additional hour that occurs when moving the clock back.

Information on prices comes from Datastream. Specifically, coal prices are represented by the API2 price traded on the London market, converted in euro using daily exchange rates also from Datastream. Gas prices are from the UK hub (NBP). Carbon dioxide prices are spot prices, taken from BlueNext (www.bluenext.eu). In cases where Bluenext values are missing, they are supplemented with carbon spot prices from Reuters. All information on prices is on a daily basis. Since fuel and carbon dioxide permits are not traded on weekends, we set their weekend value equal to the previous Friday's level.

Table 2: Summary statistics, 1 Jan 2008- 28 Aug 2012

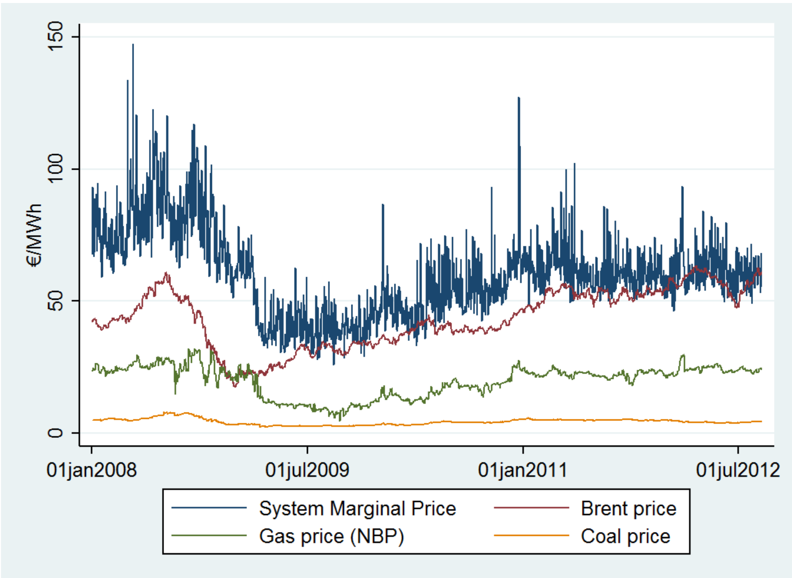
Variable	Obs	Mean	Std. Dev.	Min	Max
SMP (€/MWh)	40842	60.18	32.85	0.00	695.79
$Demand\ (MW)$	40842	4060.56	885.12	2163.78	6773.67
$Wind\ (MW)$	40842	447.43	370.15	1.68	1833.22
$Cap.Margin$	40842	3033.89	914.43	228.78	5716.73
Gas_{t-24} (€/MWh)	40824	19.65	5.81	4.57	31.78
$Coal_{t-24}$ (€/MWh)	40824	4.36	1.18	2.48	8.11
$Brent_{t-24}$ (€/MWh)	40824	42.47	10.88	17.12	62.14
Constraint payments (€)	40820	19030.94	13722.37	-37482.20	210321.00
$Wind_{FE}(MW)$	31844	-168.52	168.82	-1081.34	282.19
$Demand_{FE}(MW)$	24689	-167.60	193.53	-1309.60	732.96

Table 2 reports summary statistics for our dataset, based on hourly data. Wind generation represents 11% of demand on average in the data.

We check the stationarity of the price series. If the SMP series were non-stationary, the estimated coefficients in our analysis could be picking up a spurious relation between the SMP and other regressors, due to a potentially common trend over time. In our case, the Augmented Dickey-Fuller (ADF) test rejects the hypothesis of non-stationarity (or the presence of a unit root) in our endogenous variable, the SMP, at the 1% level.[6] The absence of a unit root is confirmed by the Im-Pesaran-Shin test for panel data (Im et al. 2003).[7]

Fig.1 shows how the SMP and the main fuel prices used in electricity generation change over time. The SMP series displays a downturn at the beginning of 2009, following the collapse of oil (and gas) prices in the summer of 2008. However, the Clemente et al. (1998) test does not find evidence of structural breaks in the SMP.[8] We also test potential breaks in the SMP series for the dates associated with SEM rule changes, highlighted in Table 1, but the Clemente and Rao tests for structural breaks show no effect for these dates.

Figure 1: *System marginal price and generation fuels, January 2008-August 2012, €/MWh*



Sources: SMP from SEMO (daily average); fuel prices (prior day) from Bloomberg

The SMP follows the price of natural gas. Natural gas plants, or more specifically Combined Cycle Gas Turbine plants (CCGT), are frequently the marginal plant, therefore setting the SMP. Differences between SMP and natural gas prices are due to losses during conversion of energy, transport, operation and maintenance costs, the cost of carbon emission permits and the cost of turning plants on and off.

Figure 2 shows how prices and demand vary by hour over the average week. The largest variation is by time of day, although weekends display lower demand and lower

[6]The associated test statistic is equal to -101.245, with the 1% critical value equal to -3.430.

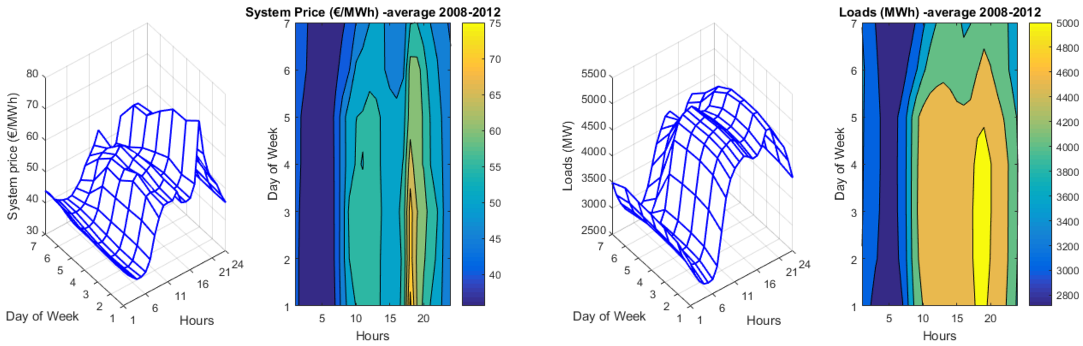
[7]The χ^2 associated to the statistic is equal to -23.46, with a test statistic equal to -1.920.

[8]The Clemente and Rao Test rejects the presence of structural break with a t-statistic equal to -32.607, with a critical value equal to -4.270. We also check the results with the Chow test, which does not find a structural break for the coefficient on wind, our main variable of interest. The coefficient on demand is the only one where the null hypothesis of no break is rejected for this test. Given the results of the Clemente and Rao and Chow tests, we decide to treat the series as a single series with no structural break.

prices.

Figure 2: *SMP and demand by day of week and hour of day, 1 Jan 2008- 28 Aug 2012*

(a) *SMP,(€/MWh)* (b) *Demand,(MWh)*



4 System marginal price: model and results

4.1 Estimation

Wind generates electricity at a low marginal price, since wind itself is free. As the amount of wind generation increases, we expect it to dampen the system marginal price. In this section we measure the extent of this effect and explore if it varies nonlinearly with wind.

Generators bid for blocks of 24 hours. Härdle and Trück (2010), Huisman et al. (2007), Guthrie and Videbeck (2007) and Weron (2008) show that in an electricity system with day-ahead bidding, hourly prices can be considered as separate contracts stipulated during the same day. Maciejowska (2014) highlights the importance of allowing flexibility in the specification of the spot price response to fuel price shocks, since the effect varies during peak and off-peak hours. Considering the hourly prices separately allows a flexible specification, where the impact of demand, wind and the other relevant variables can vary during the different hours of the day. This does not mean that prices in one hour can be analysed independently from those in adjacent hours, as prices across hours will be correlated. We estimate the SMP regression as a system of seemingly unrelated regressions (SUR), as proposed by Zellner (1962), with one equation per hour of the day and residuals correlated across the hours of the day.

We identify the effect of wind generation W on prices P by taking advantage of the hourly information on wind generation and SMP. We rely on the high variability of wind, demand and net imports, which jointly determine how much electricity is generated in each hour. We assume that demand L is exogenous, which is reasonable in this market where demand is highly inelastic to price (in part because retail prices do not vary at high frequency) and demand varies substantially during the day. This implies that in practice we do not have to worry about simultaneity problems.

We do however have to represent supply-side effects carefully. Some supply-side variables affect the marginal price directly, for example the fuel prices. We include the price of natural gas and the cost of CO_2 emission permits, represented by F^j, where j indexes the type of price. Other variables affect the price through the merit order, for example the level of plant outages and net imports.

Net imports (I) can be considered exogenous in our analysis: transmission rights to trade power along the Moyle interconnector are acquired ahead of time during our period of analysis. Moreover, McInerney and Bunn (2013) show that interconnector flows do not respond to contemporaneous electricity prices. The capacity margin mar measures the effect of both forced and unforced outages. It is defined as the difference between available capacity in every period (excluding wind, which is not predictable) and demand. The more plants are available relative to demand (the larger the capacity margin mar), the lower the system price, as cheaper plants will enter the merit order. We also measure specific outages. During the study period the pumped storage plant, Turlough Hill, and the interconnector between Northern Ireland and Scotland, Moyle, were on extended outages. Turlough Hill was on outage for about 40% of our study period, including all of 2011. Moyle was on outage about 11% of the periods. Pumped storage is a very flexible generation technology that does not actively bid in the market, is often used to balance the system and might be used to compensate for wind fluctuations (Meibom et al., 2011). Without pumped storage, the system operator has to rely more on other plants to balance supply with demand, potentially changing wind's effect on the SMP. We include dummies to account for the outages of the Moyle interconnector and Turlough Hill and their interaction with wind.

The dummy variables D^s account for several factors. For three months in 2012 (from the 27th of February to the 25th of May) generators were allowed to double the level of CO_2 emission prices in their bids (see Table 1). We control for the higher prices during this period by including a CO_2fee dummy variable. The dummies also take into account the exceptionally high demand registered between the 20th and the 22nd of December 2010, due to extremely low temperatures and the intensive use of electric heaters. Finally, the long period of our analysis (4 years) means that we have to control for other aspects of the market that change over time, including the commissioning or decommissioning of plants and regulatory changes, although on the latter see the discussion of Table 1. We do so by including month-year fixed effects.

For every hour i, we specify the following equation:

$$P_{i,d} = \alpha_i + \sum_{h}^{3}[\beta_{h,i} L_{i,d}^h + \gamma_{h,i} W_{i,d}^h + \theta_{h,i} mar_{i,d}^h] + \sum_j \zeta_{j,i} F_{i,d-1}^j + \sum_s \kappa_s D_i^s + \chi I_{i,d} + \epsilon_{i,d} \quad (1)$$

We are not interested in the coefficients for the month-year fixed effects, so we transform Eq.(1) by taking the difference of the variables from their month-year mean. This allows us to estimate the following system of equations:

$$\begin{cases} P_{1,d} = \sum_{h}^{3}[\beta_{h,1}L_{1,d}^h + \gamma_{h,1}W_{1,d}^h + \theta_{h,1}mar_{1,d}^h] + \sum_j \zeta_{j,1}F_{1,d-1}^j + \sum_s \kappa_s D_1^s + \chi I_{1,d} + \epsilon_{1,d} \\ ... \\ P_{i,d} = \sum_{h}^{3}[\beta_{h,i}L_{i,d}^h + \gamma_{h,i}W_{i,d}^h + \theta_{h,i}mar_{i,d}^h] + \sum_j \zeta_{j,i}F_{i,d-1}^j + \sum_s \kappa_s D_i^s + \chi I_{i,d} + \epsilon_{i,d} \\ ... \\ P_{n,d} = \sum_{h}^{3}[\beta_{h,n}L_{n,d}^h + \gamma_{h,n}W_{n,d}^h + \theta_{h,n}mar_{n,d}^h] + \sum_j \zeta_{j,n}F_{n,d-1}^j + \sum_s \kappa_s D_n^s + \chi I_{n,d} + \epsilon_{n,d} \end{cases} \tag{2}$$

where: $corr(\epsilon_{i,d}, \epsilon_{-i,d}) \neq 0$; $corr(\epsilon_{i,d}, \epsilon_{i,d-1}) \neq 0$; $\epsilon \sim N(\mu, \sigma^2 V)$ and V is the variance-covariance matrix.

There are $n = 24$ equations in the system, one for every hour of the day, with i indexing hours and d days. We allow wind, demand and capacity margin to have a flexible specification by including them in levels, squared and cubed (h =1-3). We expect the system price to be affected more than proportionally by changes in demand when demand is already high, because significantly more expensive plants may enter the merit order. The opposite holds for high wind levels, as we expect higher levels of wind to affect the system price less.

Ignoring possible correlations of regression disturbances over time and between subjects can lead to biased coefficients in macro panels with long time series (Baltagi, 2008). We test for the presence of heteroscedasticity in the residuals in Eq. (2) with the Breusch-Pagan test, a Lagrange Multiplier (LM) test. We reject the null hypothesis of no heteroscedasticity between the residuals, with a χ^2 equal to 21114 and an associated p-value of 0. We therefore use robust standard errors.

We follow the methodology proposed by Zellner (1962) to account for the correlation between the residuals of each equation and use a two step procedure. In the first step, the system of equations described by Eq (2) is estimated by OLS. The second step estimates the parameters of the system using Feasible Generalised Least Squares (FGLS), with the variance-covariance matrix estimated in the first step.

We also test for the presence of autocorrelation in the residuals within each equation, possible as the T dimension of our system is quite high (we have 1460 observations for each hour). Using the `xtserial` test suggested by Wooldridge (2002) we reject the null hypothesis of no autocorrelation between the residuals and model the system with autocorrelation in the error term to avoid underestimating the standard errors of the coefficients.[9] The autocorrelation is accounted for by implementing a Prais-Winsten transformation with FGLS.[10]

[9]The Wooldridge test to detect autocorrelation of residuals is based on a model estimated in first differences. In this model, the underlying assumption tested is that $cov(\Delta\epsilon_{j,d}, \Delta\epsilon_{j,d-1}) = -0.5$. The χ^2 associated with the statistic is equal to 55.67. A detailed explanation of the `xtserial` test implemented by STATA is available at `http://ageconsearch.umn.edu/bitstream/116069/2/sjart_st0039.pdf`.

[10]The autocorrelated process of the residuals means that the estimation in levels with month-year dummy

As a robustness check, we estimate Eq. (2) with a time-series approach. We use the ADF and the PAC of the residuals to determine the appropriate correlation structure of the model. This analysis highlights that the residuals are both correlated between hours and days. In particular, we find that the first 5 hours of the residuals are autocorrelated, as well as the hours 22 to 26. The results of this specification are reported in Appendix B.

4.2 Estimation: results

Results for a subset of hours are shown in Table 3. All energy is expressed in GWh for ease of reporting.

Table 3 shows a significant and negative effect of wind generation on the system marginal price, as expected. The effect is larger during the day than at night, as it displaces more expensive plants during the day.

In the SEM, day-time peak demand occurs between 10 a.m. and 12 p.m. and the evening peak is between 5 and 7 p.m. (corresponding to hours 17 to 19 in our analysis). The evening peak is the overall daily peak in the winter, whereas the day-time peak is the daily peak during summer months.

The coefficients on the square and cube wind term are both significant for several hours, including during early morning hours, confirming that the effect of wind is non-linear, at least for a few hours of the day.

The outage at Turlough Hill increases the effect of wind on the SMP at night, possibly because wind generation cannot be used to pump water back up to the upper storage. Extended outages at the Moyle interconnector do not impact wind's effect at night, whereas they decrease the effect of wind for a few hours during the day.

Full results are in Appendix A, Table A1. Other variables behave as expected. Demand has a generally positive effect on SMP and has a distinct non-linear effect. The price of natural gas is positively related to electricity prices. The capacity margin has a negative effect on SMP: when demand decreases or more generation is available, electricity prices tend to be lower all else being equal.

variables and the estimation in first differences from the month-year mean are not identical. The AR(1) process involves lagging all explanatory variables. Since dummy variables do not appear explicitly in the differenced version, they are not lagged in the AR(1) adjustment. In practice the difference between the estimates is small.

Table 3: *Effect of wind on the SMP, 1 January 2008- 28 August 2012*

	$Wind$	$Wind^2$	$Wind^3$	TH_{Out}	$Moyle_{Out}$	Wind*Moyle	Wind*TH
1	0.86	-12.69**	6.32**	1.8	1.78	1.76	-1.85
	(3.02)	(4.77)	(2.13)	(1.43)	(2.59)	(1.69)	(1.29)
2	3.53	-16.54**	7.85**	2.25	1.08	2.04	-4.88***
	(3.50)	(5.69)	(2.63)	(1.48)	(2.83)	(1.96)	(1.47)
3	6.67*	-28.39***	14.44***	2.19	1.27	-1.42	-6.73***
	(3.16)	(5.11)	(2.40)	(1.66)	(2.99)	(1.97)	(1.45)
4	13.99***	-45.42***	23.09***	3.28	0.67	-1.54	-9.72***
	(3.40)	(5.65)	(2.75)	(1.76)	(3.22)	(2.18)	(1.55)
5	15.35***	-48.53***	24.75***	3.43	2.65	-1.91	-10.53***
	(3.51)	(5.89)	(2.90)	(1.78)	(3.23)	(2.28)	(1.59)
6	14.84***	-44.91***	22.32***	2.83	0.91	-2.11	-10.86***
	(4.40)	(7.64)	(3.84)	(1.94)	(3.50)	(2.66)	(1.84)
7	-5.77	-7.23	4.83	-1.03	1.49	0.4	-0.46
	(8.89)	(15.91)	(7.97)	(3.00)	(5.45)	(4.48)	(3.27)
8	-7.53	-3.04	2.13	1.04	0.29	2.67	-0.63
	(4.34)	(7.46)	(3.55)	(1.65)	(3.14)	(2.26)	(1.70)
9	-24.71**	20.03	-7.91	-0.38	-4.19	7.5	0.63
	(9.32)	(15.76)	(7.32)	(3.45)	(6.74)	(4.93)	(3.65)
10	-20.51*	1.56	1.16	-3.91	-10.86	5.58	0.54
	(9.39)	(15.62)	(7.13)	(3.44)	(6.88)	(4.96)	(3.67)
11	-30.62***	13.81	-4.15	-1.83	-11.41	6.43	3.22
	(7.65)	(12.45)	(5.59)	(2.88)	(5.88)	(4.02)	(2.97)
12	-43.96***	31.67*	-8.64	-4.8	-13.42	8.5	-4.4
	(9.95)	(15.95)	(7.08)	(3.81)	(7.86)	(5.12)	(3.74)
13	-57.31***	45.72*	-11.98	-1.15	-28.55**	16.66**	-8.82*
	(12.20)	(19.50)	(8.60)	(4.71)	(9.17)	(6.16)	(4.43)
14	-28.08***	7.00	3.52	-5.48*	-8.95	8.92*	-3.53
	(7.00)	(10.99)	(4.79)	(2.64)	(5.84)	(3.69)	(2.53)
15	-29.40***	18.94**	-6.75*	-1.77	-5.51	7.90**	1.92
	(4.75)	(7.34)	(3.18)	(1.61)	(4.34)	(2.62)	(1.71)
16	-28.67***	18.36*	-6.54	-3.02	-5.49	7.06**	2.19
	(4.99)	(7.75)	(3.39)	(1.67)	(4.39)	(2.73)	(1.77)
17	-14.04	-13.27	8.99	-0.86	2.36	-1.05	0.78
	(8.12)	(12.81)	(5.63)	(3.06)	(6.45)	(4.25)	(2.91)
18	4.37	-76.11*	34.82**	-0.51	14.64	-20.09*	8.79
	(18.88)	(29.79)	(13.05)	(7.98)	(17.02)	(9.89)	(7.09)
19	-26.77	-6.96	6.46	15.31*	-21.3	-7.75	-12.66*
	(15.18)	(24.11)	(10.59)	(6.36)	(12.93)	(7.80)	(5.74)
20	-40.68**	14.66	-2.14	-11.74	-17.51	-9.19	-7.15
	(14.42)	(23.02)	(10.15)	(6.26)	(13.77)	(7.37)	(5.59)
21	-38.57***	28.49	-11.24	-6.66	-15.92	2.65	1.26
	(11.26)	(18.30)	(8.18)	(4.59)	(8.99)	(5.66)	(4.29)
22	-18.72*	4.7	-0.8	1.28	1.99	0.88	2.07
	(8.23)	(13.40)	(5.99)	(3.32)	(6.43)	(4.10)	(3.13)
23	-17.69***	10.93	-3.18	-0.31	2.77	0.65	1.32
	(5.18)	(8.45)	(3.79)	(2.03)	(3.91)	(2.59)	(1.95)
24	-10.29*	4.67	-1.94	-0.77	1.06	2.44	0.84
	(4.54)	(7.47)	(3.41)	(1.81)	(3.43)	(2.29)	(1.71)

Standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Wind measured in GWh. Specification accounts for month-year fixed effects and all variables listed in Equation 2.

4.3 Marginal Effects

Equation 3 outlines how we calculate the marginal effect of wind, demand and capacity margin on the system marginal price to assess their overall impact and compare our results to papers that do not analyse the relations separately for each hour or model the relations as linear.

$$\text{Marginal Effect}_i = \alpha_i + 2\beta_i\bar{i} + 3\gamma_i\bar{i}^2 + \delta_w \cdot \bar{TH} \cdot I^w + \zeta_w \cdot \bar{M} \cdot I^w \tag{3}$$

where i is the variable of interest (wind, demand or capacity margin), $\bar{i}$ is its mean value; α, β and γ are the coefficients of the variable in levels, the quadratic term and the cubic term respectively. We also include the interaction of wind and the Moyle and Turlough Hill outages, with I^w equal to 1 when i is wind and 0 otherwise.

The standard errors of the marginal effects in Table 4 are calculated using the delta method.[11] Significance of the hourly marginal effects reflects the joint significance of the linear, squared and cubic terms of the variables (wind, demand, and capacity margin), which may differ from the significance of the variables considered separately in Table 3. The marginal effect of wind on the SMP, averaged over the 24 hours, is equal to -17.25. When the average is weighted by each hour's average demand, the average is -18.17. For every MWh increase in wind generation (equal to about 0.2% of the average wind generation in our sample) the system marginal price decreases by €0.018/MWh, or about 0.03% of its average value in our sample, equivalent to an elasticity of -0.13 calculated at the mean. At the demand average of 4061MWh, this corresponds to a reduction of hourly wholesale costs to electricity buyers equal to €73.78.

We replicate the analysis for the period starting on 1 November 2009, for consistency with the constraint payment analysis (where the dataset is shorter). This leads to a demand-weighted average effect of 1MWh of wind equal to €-15.37. The average hourly demand for this period is 4014MWh, leading to a total reduction in average hourly costs to electricity buyers of €61.68 per MWh of wind for the period.

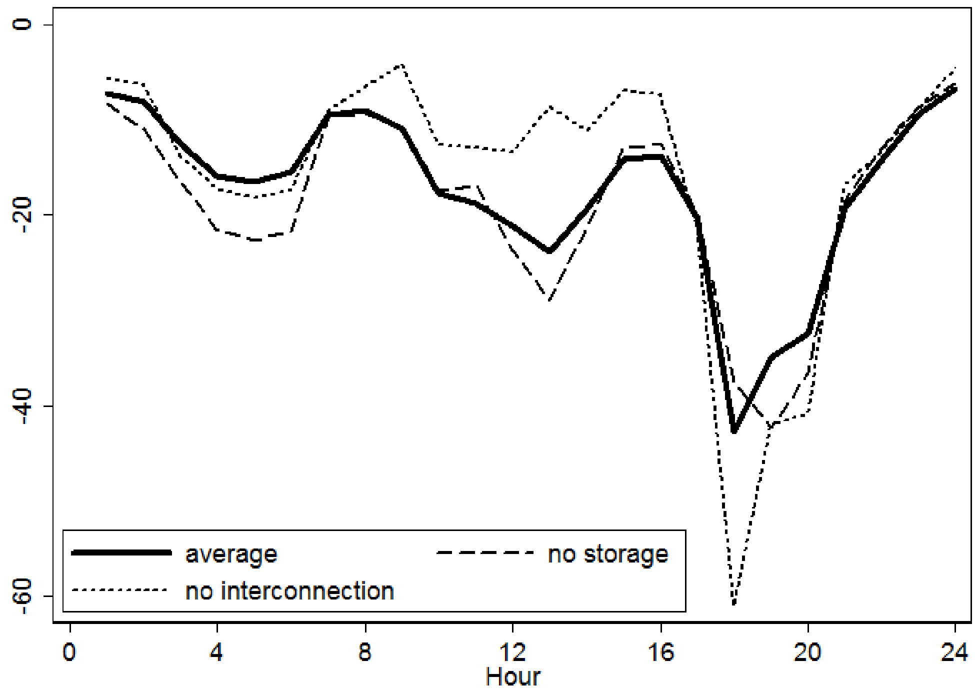
[11] This is implemented with the STATA14 `lincom` command. The delta method takes the first order Taylor approximation of the mean of the considered variables, and then calculates their variance.

Table 4: *Marginal effects on SMP, 1 Jan 2008-28 Aug 2012*

Hour	Wind	Demand	Cap.Margin
1	-7.216***	3.644***	1.648**
	(0.78)	(1.22)	(0.65)
2	-8.213***	6.116***	1.326*
	(0.89)	(1.49)	(0.71)
3	-12.515***	6.099***	-0.028
	(0.85)	(1.39)	(0.67)
4	-15.892***	8.424***	-0.162
	(0.91)	(1.51)	(0.71)
5	-16.489***	8.954***	-0.491
	(0.94)	(1.5)	(0.7)
6	-15.428***	11.343***	-0.967
	(1.12)	(1.67)	(0.82)
7	-9.437***	4.072*	-4.993***
	(2.11)	(2.45)	(1.46)
8	-8.986***	8.598***	-3.468***
	(1.08)	(0.96)	(0.85)
9	-11.039***	11.888***	-4.663**
	(2.34)	(2.1)	(2.01)
10	-17.784***	6.887***	-10.62***
	(2.36)	(2.16)	(1.97)
11	-18.808***	5.017***	-10.127***
	(1.92)	(1.85)	(1.6)
12	-21.167***	-0.322	-14.613***
	(2.47)	(2.56)	(2.08)
13	-23.826***	-10.049***	-18.73***
	(3.03)	(3.19)	(2.45)
14	-19.337***	-3.875*	-10.253***
	(1.76)	(2.03)	(1.49)
15	-14.14***	6.487***	-7.959***
	(1.21)	(1.36)	(1.05)
16	-13.837***	7.499***	-7.741***
	(1.25)	(1.32)	(1.09)
17	-20.347***	14.276***	-9.667***
	(1.99)	(1.97)	(1.72)
18	-42.702***	42.714***	-20.636***
	(4.61)	(4.92)	(4.41)
19	-34.94***	35.443***	-8.537**
	(3.66)	(3.89)	(3.45)
20	-32.433***	29.67***	-11.722***
	(3.5)	(4.1)	(3.58)
21	-19.206***	19.641***	-6.897***
	(2.71)	(2.83)	(2.5)
22	-14.124***	6.956***	-7.449***
	(1.98)	(2.13)	(1.78)
23	-9.353***	0.405	-4.378***
	(1.24)	(1.5)	(1.04)
24	-6.75***	1.934	-0.738
	(1.1)	(1.47)	(0.9)
Average	-17.249	10.943	-8.394
Demand weighted average	-18.169	10.136	-7.501

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Variables measured in GWh. Averages calculated on marginal effects significantly different from 0 at the 10% level.

Figure 3: *Marginal effect of wind on SMP, €/GWh of wind*



The no storage and no interconnection scenarios set the relevant outage dummy to 1.

Figure 3 shows how the marginal effect of wind on the SMP would change if we assumed that the pumped storage plant and the interconnector were on outage for the whole period of analysis. To calculate the effect of wind in this scenario we set the Turlough Hill (Moyle interconnector) outage dummy to 1 and consider all other variables at their hourly average. The demand-weighted average effect of 1MWh of wind when the pumped storage plant is on outage is €-18.67/GWh and when the interconnector is on outage is €-17.28/GWh. These are similar to the -18.17 shown in Table 4. There are however some changes in the hourly effects. Without storage, the effect of wind on SMP is stronger during early morning hours. These are times when wind tends to blow more. In the absence of storage, the additional wind cannot be used to pump water up to the upper basin. During the day, the pattern without interconnection shows a weaker effect of wind on the SMP perhaps because on average the interconnection flow is displacing less expensive rather than more expensive generation during the day, so in the absence of interconnection the SMP is smaller and the effect of wind is also smaller.

Figure 4 shows how these results compare to a few recent estimates of the effect of wind on spot prices. For each estimate, we calculate the implied percentage change in spot price due to a 1MWh increase in wind generation and present its absolute value (all papers estimate a negative relation between wind generation and spot price). We caution that comparing across studies is difficult, given differences in market design, generation mix and estimation strategies. In particular, not all transactions occur in the spot market in some jurisdictions (e.g. Germany and the Netherlands). The spot price is the real-time price in Australia, which is an energy-only market. In Germany, Netherlands, Italy and Ireland it is the day-ahead price. Moreover some jurisdictions display a concurrent increase in solar generation, which may depress spot prices on its own in addition to limiting wind's impact. In the SEM during this period there was essentially no solar power, which is also true for the Netherlands. In Germany solar generation increased from 1% to 5% of demand in the 2008-2012 period. In Italy the solar share increased even more, going from essentially 0 to more than 6% of demand. Finally, markets in continental Europe are more interconnected, which may affect the impact of wind generation.

Figure 4: *% spot price change with 1MWh increase in wind generation*

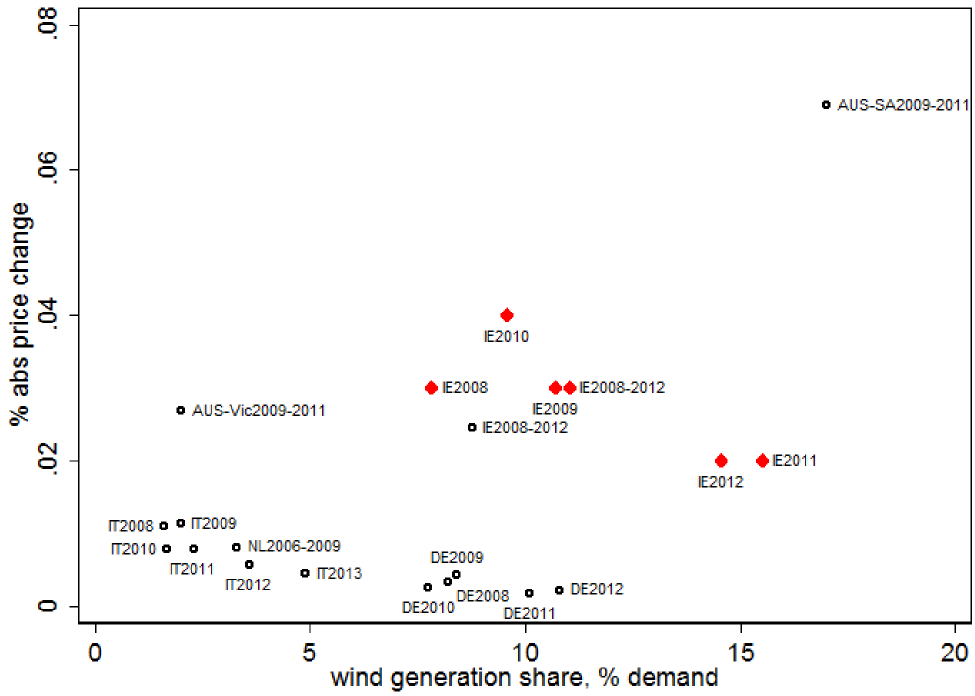


Table C3 in the Appendix reports the underlying data.
DE=Germany; IE=Ireland; IT=Italy; NL=Netherlands; AUS-SA=Southern Australia; AUS-Vic=Victoria

We can make 2 observations. First, our estimates (red diamonds) are the largest for European countries, but are significantly smaller than the estimates for Southern Australia. Second, within each study (country) the size of the effect tends to decrease over time as wind penetration increases, suggesting a non-linear and decreasing impact of wind generation. Our result is slightly higher than the value found for Ireland by Swinand and O'Mahoney (2015), who use a different specification and approach.[12]

[12] In particular, Swinand and O'Mahoney (2015) focus on wind in the Republic of Ireland alone, use a different All-Ireland demand variable, include the wind forecast error as a determinant of the spot price and use a different specification.

For a review of both simulation and econometric studies prior to 2011 see Würzburg et al. (2013).

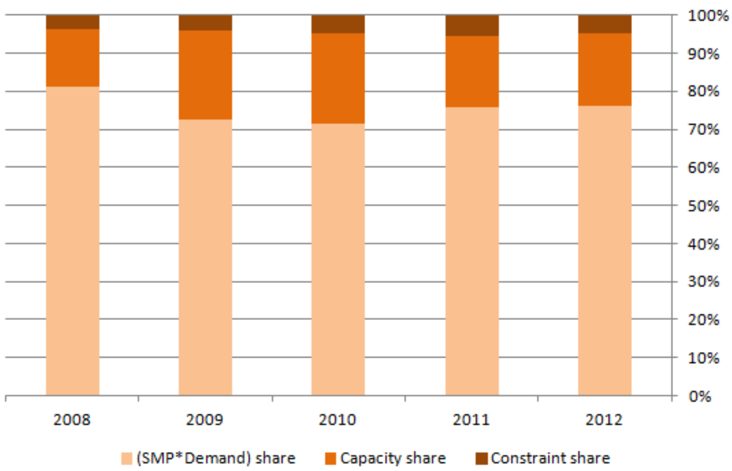
5 Constraint payments: model and results

In the SEM, initial dispatch is based on the day-ahead bids, forecasts of wind, demand and plant availability and a simplified representation of generators' technical constraints. It does not consider transmission and distribution constraints. There is no intraday market in SEM, and the positions are all adjusted in the balancing market.

There are four main reasons why real-time dispatch may differ from the day-ahead plans and give rise to constraint payments. First, system operators do not have perfect foresight. There will therefore be real-time adjustments to account for unexpected changes in supply or demand, for example when capacity is not able to deliver. Second, in the presence of network constraints, some plants will have to generate less and others more than the market schedule to avoid surcharging transmission and distribution lines. Third, the system operator has to meet other system constraints, for example the maintenance of voltage and frequency stability throughout the system, which may change which plants actually generate. Finally, the cost-minimizing algorithm in the day-ahead market does not take into account all possible technical characteristics of the generators, whereas during actual dispatch the TSOs (and generators) are meeting all the technical requirements.

Constraint payments are assigned by the TSO to the generating units and have been growing over time, as shown in Figure 5. In 2008 they accounted for about 4% of system costs, calculated as the sum of the system marginal price times demand, constraint payments and capacity payments, rising to 6% in 2011 before falling back to 5% in 2012.

Figure 5: *Total system cost component shares, 2008-2012*



$$Total\ System\ Costs = Constraint\ Payments + Capacity\ payments + SMP \cdot Demand$$

5.1 Constraint payments: model

The determinants of constraint payments CP at time t ideally include indicators for transmission constraints TC, forced outages at predictable generation plants (such as thermal plants) $ForOut$, wind and demand forecast errors and fuel prices $\mathbf{P_t}$. An increase in constraint payments could also be due to the unplanned outage of the Turlough Hill power plant. Operation of the pumped storage plant is particularly relevant, since it is used heavily to compensate for short-run imbalances in the system. The interconnector is also at times used by system operators to balance demand, although most of the evidence suggests that the Moyle interconnector is not used to optimise short-run operations (McInerney and Bunn, 2013). This would lead to a specification of the following form:

$$CP_t = f(TC_t, ForOut_t, WindFE_t, DemandFE_t, \mathbf{P_t}) \tag{4}$$

Unfortunately, we do not have detailed information for all the explanatory variables in Equation 4. We are unable to account directly for transmission constraints, although we know that some plants are constrained on to avoid chronic transmission constraints that also affect system stability.[13] There are also three main system-wide constraints. The first is a voltage constraint for the Dublin area involving three plants: Poolbeg combined cycle, Dublin Bay Power and Huntstown combined cycle. The second is a system inertial stability constraint, which requires 5 large units on at all times and affects large inflexible units like the Moneypoint coal power plant. The last constraint requires some plants (like the CCGT plants at Whitegate and Tynagh) to be kept on as operating reserve. To control for the constraint payments associated with these constraints, which are independent of wind generation, we set the constraint payments associated with these particular plants equal to 0 when they are negative (i.e. when the plant was slated to run but did not because the transmission or system constraint did not take place).

We do not have hourly information on forced outages separately from planned maintenance, but we account for large periods of well-documented forced outages at two plants, the pumped storage plant at Turlough Hill and the Moyle interconnector.

To model the lack of perfect foresight by the system operator, we include both wind and demand forecast errors. We focus on the forecast error from the day-ahead market (24 hours ahead), as it is the most relevant in the case of the SEM. The forecast errors are the difference between the actual outturn and the values expected in the day-ahead market, or $x_t - x_{t-24}$, where x is either wind generation or demand.

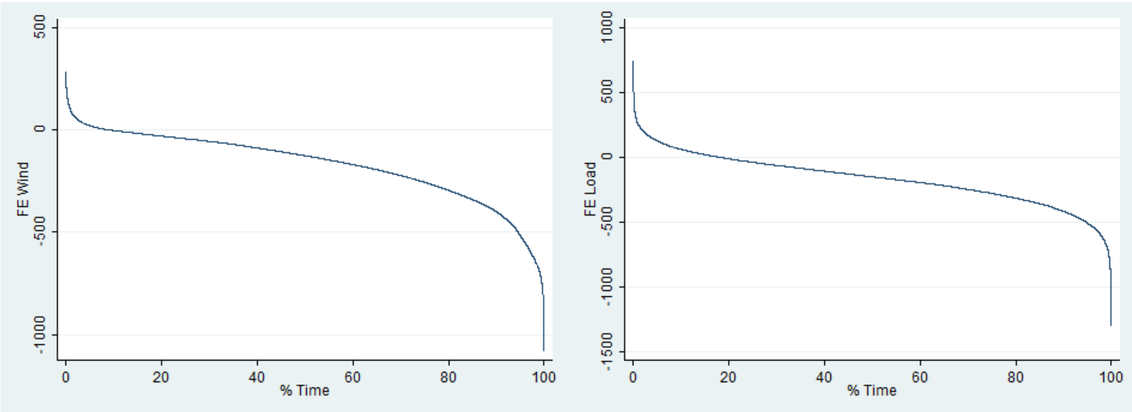
The day-ahead market appears to systematically over-estimate both system demand and wind generation, as shown in Figure 6. Wind is forecasted to be larger than its actual outturn for 29018 observations (91% of the total), against the 2825 periods when it is forecast to be lower (9% of the cases). The wind series we use in the estimation is net of wind curtailment, but wind curtailment tends to be associated with periods of high wind

[13] More details available at: `http://www.eirgrid.com/media/Power%20System%20Seminar%204.pdf`, pg.52.

generation.[14] Demand is forecasted to be higher than actual outturn 20335 times (82% of the cases) and lower only 4356 times, or 18% of the cases. This may result in increasing balancing costs. Mauch et al. (2013) report a similar asymmetry for US wind forecasts. At times of low wind, forecasts tend to underestimate wind generation, whereas the forecasts tend to overestimate wind generation when it blows strongly, thereby overestimating wind generation on average since the errors are proportional to the amount of wind.

Figure 6: *Duration curve of the forecast errors, 1 Nov 2009- 28 Aug 2012*

(a) *Wind, (MW)* (b) *Demand,(MW)*



Forecast errors are defined as: $FE_{w,l} = Actual_{w,l} - Forecasted_{w,l}$

Plants that are constrained down return their unrealised costs to the system, while keeping the period's system marginal price. In other words, they keep the inframarginal rent for every period they were scheduled to run in the day ahead market, but were told not to run due to system constraints. Plants that are constrained up receive payments for their costs, but no additional payments.

Typically the cheaper plants are scheduled in the day ahead, so we expect the positive constraint payments to be larger than negative constraint payments on average. In any given period we might observe negative constraint payments, for example if demand turns out to be lower than expected (some plants will be returning their unrealised costs and no plants will generate in their place) or wind generation turns out to be higher than expected as wind's generation costs are close to zero.

Based on data availability, as discussed above, we measure the effect of wind (and the associated wind forecast errors) on the size of constraint payments and estimate the following specification (reported as Model 1 in Table 5), using autocorrelated residuals to account for system dynamics. We account for unobserved but exogenous changes over time by including month-year fixed effects and estimate the following equation, where the variables are differenced with respect to their month-year average:

[14]During this period some wind was dispatched down for both system-wide reasons and local grid congestion, although we are unable to distinguish between the two causes. For 2012, EirGrid and SONI (2013a) report that 2.1%, or 110GWh, were curtailed, similar to the 2.2% and 119GWh curtailed in 2011 (EirGrid and SONI, 2012).

$$
\begin{aligned}
CP_t = \beta_1 L_t + \beta_2 W_t + \beta_3 Wind_F E_t + \beta_4 Demand_F E_t \\
+\beta_5 mar_t + \beta_6 \mathbf{P_t} + \beta_7 Out^n + \sum \kappa^s D_t^s + \epsilon_t
\end{aligned} \tag{5}
$$

where $\epsilon_t = \sum_{i=1}^{4} \rho_i \epsilon_{i,t} + \sum_{i=21}^{24} \rho_i \epsilon_{i,t}$.

CP_t are the system constraint payments that arise each hour t, calculated as the sum of each plant's constraint payments and adjusted for system constraints as discussed earlier; L represents system demand. We expect that the larger the demand, the higher the probability of congestion on transmission lines and so the larger the constraint payments. The more wind W on the system, the larger the forecast errors and the higher the probability of congestion, so we expect wind to have a positive effect on constraint payments. $\mathbf{P_t}$ includes the price of natural gas, which is the most frequent marginal fuel, and the price of carbon dioxide permits. The larger these prices the higher we expect constraint payments to be. The set of dummy variables D include the outages of the Moyle interconnector and the Turlough Hill pumped storage plant and their interaction with wind generation. When the capacity margin mar is high, there are many plants available to increase generation. We therefore expect that if the dispatch changes, it will likely be at lower cost to the system, so we expect the capacity margin to have a negative effect on constraint payments.

We use the autocorrelation and partial autocorrelation graphs to determine that the first 4 hours and the day-ahead residuals are autocorrelated, as well as the residuals for hours 21 to 24. The autocorrelated residuals capture some of the inertia of the system, as it takes plants a few hours to turn on or shut down.[15]

5.2 Estimation results

Results for Model 1 in Table 5 shows that neither demand nor capacity margin are significantly different from zero, suggesting that the tightness of the market does not drive constraint payments. Higher natural gas prices are associated with higher constraint payments, as expected.

The coefficient on the demand forecast error is significant and positive. When demand in the system is higher than expected, more plants will need to generate and be paid to match demand. The coefficient on the wind forecast error is negative: when actual wind generation is higher than forecasted, constraint payments will be lower. When unexpected wind generation enters the system it displaces plants with a marginal cost of generation higher than wind. When the unrealised costs of more expensive plants are returned to the market, they lower constraint payments. The opposite is true when the wind is lower than forecasted.

[15] We account for autocorrelation of the residuals using Stata 14's ARIMA command, which uses a Kalman filter specification. Including an AR specification of the residuals is equivalent to a common factor specification of system dynamics (see e.g. Greene, 2003, page 609 and following).

Table 5: Effect on constraint payments(€), 1 Nov. 2009- 28 Aug. 2012

	Model 1	Model 2
Gas_{t-24} €/MWh	388.782*	403.787*
	(178.361)	(179.287)
Demand MWh	-0.690	-0.707
	(0.504)	(0.507)
Wind MWh	3.200***	2.624**
	(0.833)	(0.831)
$Demand_{FE}$	4.004***	
	(0.911)	
$Wind_{FE}$	-4.366***	
	(0.735)	
$Wind_{FE}^{Negative}$		-4.821***
		(0.805)
$Wind_{FE}^{Positive}$		3.446
		(6.335)
$Demand_{FE}^{Negative}$		2.849**
		(0.971)
$Demand_{FE}^{Positive}$		0.230
		(2.117)
*Tur. Hill Out * Wind.Gen*	2.987***	2.989***
	(0.867)	(0.869)
Tur.Hill Outage dummy	-2329.870*	-2281.927*
	(1074.694)	(1076.319)
Moyle Outage dummy	819.369	674.700
	(1508.573)	(1525.626)
*Moyle Out * Wind.Gen*	0.299	0.379
	(0.731)	(0.737)
Generation Margin (€/MW)	0.849	0.804
	(0.441)	(0.442)
CO_2 Price, €/tonne	53.928	47.029
	(285.092)	(287.309)
AR(1)	0.175***	0.176***
	(0.003)	(0.003)
AR(2)	0.090***	0.090***
	(0.004)	(0.004)
AR(3)	0.036***	0.037***
	(0.006)	(0.006)
AR(4)	0.039***	0.039***
	(0.007)	(0.007)
AR(21)	0.018***	0.019***
	(0.005)	(0.005)
AR(22)	0.009*	0.010*
	(0.004)	(0.004)
AR(23)	0.094***	0.095***
	(0.003)	(0.003)
AR(24)	0.161***	0.162***
	(0.003)	(0.003)
Constant	12823.713***	12824.970***
	(18.732)	(19.433)
Observations	24499	24499

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1
Variables are defined as deviation from their month-year mean.

Table 5 also shows that the outage of the interconnector has no effect on constraint payments, whereas when Turlough Hill is on outage, constraint payments decrease. This is counter intuitive. It may be that at times when the pumped storage plant is not on line, more thermal plants are dispatched in the day-ahead market, leading to a higher probability that thermal plants are constrained down in the realtime market. On the other hand, when Turlough Hill is on outage, wind generation has an effect that is both stronger in statistical terms and more than twice as large, implying that at these times a MWh of wind generation increases constraint payments by almost €6.

As a robustness check we allow the forecast errors to have a separate effect if they are negative or positive and report the results under Model 2. Both the demand and the wind forecast errors are significant only when they are negative (when the realised value is smaller than the forecast). The coefficient on the negative forecast error is somewhat smaller than in Model 1, whereas the coefficient on the negative forecast error for wind is somewhat larger in absolute value. The other results remain essentially the same. More wind increases constraint payments, although by a bit less than in Model 1, and the outage at the pumped storage plant also increases the effect of wind on constraint payments.

Overall we find that wind generation is positively related to constraint payments, all other things being equal (including the level of wind forecast error). After controlling for other variables, every MWh of additional wind generation is associated with an increase in constraints payments of €3.2 in our Model 1 estimation, corresponding to about 0.012% of hourly constraint payments.

Hirth and Ziegenhagen (2015) and Gianfreda et al. (2016) find that balancing payments decrease with high levels of renewable generation in Germany and Italy, possibly because these markets include active intra-day trading, which is not in place in the SEM between 2008 and 2012. However, Chaves-Ávila and Fernandes (2015) report that intra-day trading is active in the Spanish market, but Batalla-Bejerano and Trujillo-Baute (2016) find that renewables still increase balancing costs. Their estimate of the short-run elasticity of balancing payments to renewable generation (wind and solar) in Spain is between 1% and 5%. Our estimates suggest that a 0.2% increase in wind leads to a 0.012% increase in constraint payments, for an elasticity of about 5%. When storage is on outage the elasticity increases to 13%.

6 Wind subsidies

Energy policy in the Republic of Ireland and Northern Ireland includes subsidies for electricity generated by wind. In Ireland this takes the form of a feed-in tariff, called REFIT, which applies for 15 years to each renewable generator. Northern Ireland uses renewable obligation certificates (ROCs), designed to help the UK meet its renewable energy targets. These are granted to renewable generators for 20 years.

We calculate the cost of wind support in Ireland by measuring the REFIT payments to onshore wind generation during our period of analysis. The REFIT scheme provides a guaranteed price to renewable generators (or suppliers they enter into long term contracts with). The 2006 version of the program, that we focus on here, offered different levels of guaranteed prices, depending on the size of wind farms. For wind farms with less than 5MW export capacity, the guaranteed payments were slightly higher, as shown in Table 6.[16]

Table 6: REFIT guaranteed price, €/MWh (nominal)

Fiscal year	Large Wind	Small wind
2008	63.739	65.976
2009	66.353	68.681
2010	66.353	68.681
2011	66.353	68.681
2012	68.078	70.467

Small wind has export capacity $\leq$ 5MW

Source: DCENR

Fiscal year is from 1 Oct. of prior year until 30 Sep.

The REFIT regime provides a fixed payment equal to 15% of the guaranteed price of electricity for large wind farms, plus a top up if the average yearly price wind generators receive from the market (equal to the sum of the SMP and capacity payments) is below the guaranteed price.

The value of REFIT over the whole 2 January 2008 to August 28 2012 period per MWh of onshore wind is about €15.3/MWh. These payments are passed on to final consumers through the public service obligation (PSO), assessed by the Commission for Energy Regulation each fiscal year. Section Appendix D gives the details on the data and the calculation of the average REFIT cost per MWh.

ROCs in Northern Ireland work differently. Each renewable generator is assigned a number of ROCs based on its generation. During our period of analysis, wind generators in Northern Ireland were allocated 1 ROC per MWh of generation. Companies that supply electricity to consumers have to buy a minimum share of renewable energy and they can comply either by turning over an appropriate number of ROCs to the regulatory body or by paying a buy-out fee for every MWh of renewable generation needed to reach the minimum level and not covered by ROCs.[17] The cost of the ROCs is passed on to final consumers. Here we consider the buy-out fee as the cost paid by consumers.[18] Table 7 reports the buy-out fee in each fiscal year during the period of our study. It is more than 3.5 times larger than the cost of REFIT per MWh. This is consistent with other analyses comparing the renewable subsidy costs in the two jurisdictions (Deane et al., 2015) and

[16]DCENR source accessed July 2016 at http://www.dcenr.gov.ie/energy/SiteCollectionDocuments/Renewable-Energy/RefitReferencePrices.pdf

[17]The initial legislation on ROCs in Northern Ireland was passed in 2006 with the Renewables Obligation Order (Northern Ireland) 2006. Details on ROCs in Northern Ireland can be found at https://www.economy-ni.gov.uk/articles/northern-ireland-renewables-obligation

[18]For an explanation of why the buy-out fee is reasonable approximation of the cost of ROCs to consumers, see for example Bryan et al. (2015).

may be one of the reasons the UK is moving to a feed-in tariff support system starting in 2017.

Table 7: Buy-out fee for Northern Ireland ROCs, nominal

	£/MWh	exchange rate	€/MWh
2008/09	35.76	0.9308	38.42
2009/10	37.19	0.8898	41.80
2010/11	36.99	0.8837	41.86
2011/12	38.69	0.8339	46.40
2012/13	40.71	0.8469	48.07
Average	37.87		43.31
Avg. from 2009	38.40		44.53

Source: Ofgem (2012); fiscal year in the UK is from 1 April to 31 March. Exchange rates for March 31 from www.ecb.europa.eu

This cost should be interpreted as the cost to consumers of an additional MWh of wind generation, rather than the average cost of wind generation subsidies. Over time the subsidy expires (after 15 years for REFITs and 20 years for ROCs) whereas wind farms may continue generating.

To summarise, for the period starting November 1 2009, an additional MWh of wind generation increases constraint payments by an estimated €3 (or €6 when the pumped storage plant is on outage), but decreases total electricity purchase costs by about €62. Consumers in the Republic of Ireland subsidise this wind by an average €15/MWh, suggesting a positive net effect of about €43/MWh, decreasing to €40/MWh when storage is not available. Consumers is Northern Ireland pay about €45/MWh in subsidies, for a positive net effect of €13/MWh, decreasing to €10/MWh when storage is on outage.

These results contrast with results for Spain after 2010 (Ciarreta et al., 2014) where wind increases net costs to consumers. The average subsidy in Spain is about €75/MWh of wind or higher from 2009 onward, which is significantly larger than both the subsidy in Ireland and in Northern Ireland. For Denmark Munksgaard and Morthorst (2008) state that the subsidy decreased from €66 in 2000 to €12 per MWh of wind in 2006, leading to a slight net cost to consumers by 2006 between €3 and €7 per MWh of wind.

7 Conclusion

This paper analyses how wind generation influences the price and constraint payments in the Irish Single Electricity Market and compares it to the wind subsidy paid by consumers.

To define the impact on the system price, we estimate a system of hourly equations and find a consistent negative effect of wind. We show that the effect is not linear and is affected by the presence (or rather, absence) of storage. When Turlough Hill, the largest storage facility in the SEM, is on outage, the impact of wind on prices increases at night, possibly because wind cannot be used to pump water back of to the upper storage. Outages at the interconnector between the island of Ireland and Great Britain lead to a decreased impact during some hours of the day. We calculate the average effect of wind on prices and show that a MWh increase in wind generation (equal to about 0.2% of the average wind generation in our sample) leads to a decrease of the system marginal price equal to €0.018/MWh, or about 0.03% of its average value in our sample.

Second, we investigate if and how wind affects constraint payments. Our prior is that larger amounts of wind lead to higher constraint payments, all else being equal. This is confirmed by our findings that show that wind generation is positively linked to constraint payments both directly and through the wind forecast error. The larger the errors in forecasting the level of wind and demand, the larger the constraint payments. In periods when storage is unavailable, the impact of wind generation on constraint payments more than doubles. We find no systematic effect of outages at the interconnector between the island of Ireland and Great Britain on constraint payments.

Finally, we calculate the cost of subsidies for wind generation, which differ in Northern Ireland and in Ireland. Once we consider the cumulative effect of changes in wind generation on the spot price, the constraint payments and the cost of subsidies, we conclude that the net effect is positive for the SEM during our period of analysis, although the positive effect is larger for consumers in the Republic of Ireland than for consumers in Northern Ireland, due to different subsidy schemes. When pumped storage is on outage the constraint payments increase significantly, but the net effect remains positive in both jurisdictions.

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Appendix A Estimation results

Table A1 below shows results for all hours estimated following Equation 2. CO_2 price and CO_2 fee (measured in €/tonne) are not presented due to space limitations; complete results are available from the authors upon request. Wind, demand, capacity margin and imports are in GWh. Price of gas is in €/MWh.

Table A1: *SMP (€/MWh): 1 January 2008- 28 August 2012*

	$Wind$	$Wind^2$	$Wind^3$	TH_{Out}	$Moyle_{Out}$	Wind · Moyle	Wind · TH	$Demand$	$Demand^2$	$Demand^3$	Cap.Margin	$Cap.Margin^2$	$Cap.Margin^3$	Gas_{t-24}	Imports
1	0.86	-12.69**	6.32**	1.8	1.78	1.76	-1.85	-40.33	11.7	-1.03*	-93.41***	26.72***	-2.50***	0.89***	0.00
	(3.02)	(4.77)	(2.13)	(1.43)	(2.59)	(1.69)	(1.29)	(26.75)	(6.40)	(0.50)	(9.81)	(3.05)	(0.32)	(0.18)	(1.43)
2	3.53	-16.54**	7.85**	2.25	1.08	2.04	-4.88***	-75.35**	22.28***	-1.99***	-93.04***	24.90***	-2.19***	0.80***	-2.5
	(3.50)	(5.69)	(2.63)	(1.48)	(2.83)	(1.96)	(1.47)	(24.05)	(6.17)	(0.51)	(10.13)	(3.06)	(0.30)	(0.19)	(1.80)
3	6.67*	-28.39***	14.44***	2.19	1.27	-1.42	-6.73***	-17.12	7.44	-0.8	-70.94***	16.67***	-1.30***	0.78***	-4.72***
	(3.16)	(5.11)	(2.40)	(1.66)	(2.99)	(1.97)	(1.45)	(20.02)	(5.37)	(0.46)	(9.61)	(2.78)	(0.27)	(0.20)	(1.19)
4	13.99***	-45.42***	23.09***	3.28	0.67	-1.54	-9.72***	-14.08	7.59	-0.85	-66.17***	14.77***	-1.10***	0.70**	-6.71***
	(3.40)	(5.65)	(2.75)	(1.76)	(3.22)	(2.18)	(1.55)	(20.39)	(5.61)	(0.49)	(9.90)	(2.84)	(0.27)	(0.21)	(1.26)
5	15.35***	-48.53***	24.75***	3.43	2.65	-1.91	-10.53***	-11.71	7.03	-0.8	-66.53***	14.75***	-1.09***	0.62**	-7.76***
	(3.51)	(5.89)	(2.90)	(1.78)	(3.23)	(2.28)	(1.59)	(19.89)	(5.53)	(0.48)	(9.72)	(2.78)	(0.26)	(0.21)	(1.28)
6	14.84***	-44.91***	22.32***	2.83	0.91	-2.11	-10.86***	18.84	-0.86	-0.1	-51.08***	10.32***	-0.69*	0.56*	-6.58***
	(4.40)	(7.64)	(3.84)	(1.94)	(3.50)	(2.66)	(1.84)	(21.71)	(6.08)	(0.53)	(10.64)	(3.08)	(0.29)	(0.22)	(1.82)
7	-5.77	-7.23	4.83	-1.03	1.49	0.4	-0.46	-19.59	7.78	-0.85	-17.51	-1.21	0.45	0.55	-15.58**
	(8.89)	(15.91)	(7.97)	(3.00)	(5.45)	(4.48)	(3.27)	(35.17)	(9.55)	(0.82)	(17.19)	(5.16)	(0.50)	(0.30)	(4.77)
8	-7.53	-3.04	2.13	1.04	0.29	2.67	-0.63	-48.99**	16.97***	-1.66***	-76.63***	16.97***	-1.25***	1.10***	-17.57***
	(4.34)	(7.46)	(3.55)	(1.65)	(3.14)	(2.26)	(1.70)	(16.17)	(4.12)	(0.34)	(9.67)	(2.87)	(0.28)	(0.18)	(2.42)
9	-24.71**	20.03	-7.91	-0.38	-4.19	7.5	0.63	21.89	1.39	-0.43	-125.23***	30.41***	-2.31***	0.91*	-30.15***
	(9.32)	(15.76)	(7.32)	(3.45)	(6.74)	(4.93)	(3.65)	(46.70)	(11.77)	(0.98)	(18.19)	(5.93)	(0.62)	(0.38)	(5.32)
10	-20.51*	1.56	1.16	-3.91	-10.86	5.58	0.54	195.41***	-36.90*	2.34*	-95.39***	22.35***	-1.65*	0.99*	-35.37***
	(9.39)	(15.62)	(7.13)	(3.44)	(6.88)	(4.96)	(3.67)	(58.58)	(14.42)	(1.17)	(16.58)	(5.81)	(0.65)	(0.39)	(5.61)
11	-30.62***	13.81	-4.15	-1.83	-11.41	6.43	3.22	335.17***	-66.58***	4.44***	-73.49***	17.64***	-1.35*	1.00**	-31.83***
	(7.65)	(12.45)	(5.59)	(2.88)	(5.88)	(4.02)	(2.97)	(50.39)	(12.21)	(0.97)	(14.00)	(5.08)	(0.59)	(0.33)	(4.80)
12	-43.96***	31.67*	-8.64	-4.8	-13.42	8.5	-4.4	431.88***	-89.09***	6.11***	-96.08***	23.95***	-1.98*	0.85	-40.57***
	(9.95)	(15.95)	(7.08)	(3.81)	(7.86)	(5.12)	(3.74)	(66.68)	(16.12)	(1.28)	(18.06)	(6.66)	(0.79)	(0.44)	(6.49)
13	-57.31***	45.72*	-11.98	-1.15	-28.55**	16.66**	-8.82*	712.79***	-153.80***	10.91***	-74.97***	14.80*	-0.83	1.03*	-27.89***
	(12.20)	(19.50)	(8.60)	(4.71)	(9.17)	(6.16)	(4.43)	(78.64)	(19.10)	(1.52)	(20.26)	(7.53)	(0.89)	(0.51)	(7.77)
14	-28.08***	7	3.52	-5.48*	-8.95	8.92*	-3.53	453.87***	-99.07***	7.15***	-68.46***	17.87***	-1.62**	0.56	-30.05***
	(7.00)	(10.99)	(4.79)	(2.64)	(5.84)	(3.69)	(2.53)	(47.45)	(11.60)	(0.93)	(13.19)	(4.82)	(0.56)	(0.33)	(4.39)
15	-29.40***	18.94**	-6.75*	-1.77	-5.51	7.90**	1.92	273.43***	-56.69***	4.01***	-83.38***	23.05***	-2.16***	0.51*	-23.80***
	(4.75)	(7.34)	(3.18)	(1.61)	(4.34)	(2.62)	(1.71)	(32.40)	(7.82)	(0.63)	(9.79)	(3.53)	(0.41)	(0.24)	(2.40)
16	-28.67***	18.36*	-6.54	-3.02	-5.49	7.06**	2.19	254.36***	-51.89***	3.63***	-80.89***	21.95***	-2.00***	0.51*	-20.83***
	(4.99)	(7.75)	(3.39)	(1.67)	(4.39)	(2.73)	(1.77)	(32.72)	(7.77)	(0.61)	(9.96)	(3.60)	(0.42)	(0.24)	(2.47)
17	-14.04	-13.27	8.99	-0.86	2.36	-1.05	0.78	166.81***	-32.31**	2.28**	-78.87***	21.25***	-1.97**	0.66	-23.86***
	(8.12)	(12.81)	(5.63)	(3.06)	(6.45)	(4.25)	(2.91)	(46.15)	(10.67)	(0.82)	(15.01)	(5.50)	(0.64)	(0.35)	(4.87)
18	4.37	-76.11*	34.82**	-0.51	14.64	-20.09*	8.79	-182.44	28.19	-0.69	-88.77**	23.70*	-2.54	-0.06	-25.69*
	(18.88)	(29.79)	(13.05)	(7.98)	(17.02)	(9.89)	(7.09)	(104.02)	(22.58)	(1.62)	(27.94)	(11.13)	(1.40)	(0.93)	(12.99)
19	-26.77	-6.96	6.46	15.31*	-21.3	-7.75	-12.66*	-701.34***	152.62***	-10.53***	-52.90*	15.29	-1.59	1.44*	-36.46***
	(15.18)	(24.11)	(10.59)	(6.36)	(12.93)	(7.80)	(5.74)	(83.39)	(18.22)	(1.32)	(21.91)	(8.72)	(1.10)	(0.72)	(10.98)
20	-40.68**	14.66	-2.14	-11.74	-17.51	-9.19	-7.15	-753.22***	176.85***	-13.24***	-154.32***	47.37***	-4.81***	0.05	-40.22**
	(14.42)	(23.02)	(10.15)	(6.26)	(13.77)	(7.37)	(5.59)	(97.62)	(21.65)	(1.59)	(24.31)	(9.53)	(1.19)	(0.75)	(12.23)
21	-38.57***	28.49	-11.24	-6.66	-15.92	2.65	1.26	-123.75	44.51**	-4.18***	-92.91***	24.28**	-1.88*	1.05*	-32.18***
	(11.26)	(18.30)	(8.18)	(4.59)	(8.99)	(5.66)	(4.29)	(67.64)	(15.38)	(1.17)	(20.57)	(7.62)	(0.91)	(0.50)	(8.27)
22	-18.72*	4.7	-0.8	1.28	1.99	0.88	2.07	52.66	-2.59	-0.38	-98.35***	23.75***	-1.65*	1.07**	-12.43*
	(8.23)	(13.40)	(5.99)	(3.32)	(6.43)	(4.10)	(3.13)	(48.54)	(11.54)	(0.92)	(17.34)	(6.12)	(0.70)	(0.36)	(6.08)
23	-17.69***	10.93	-3.18	-0.31	2.77	0.65	1.32	104.78***	-25.76***	2.12***	-63.49***	15.51***	-1.22**	0.83***	-12.31***
	(5.18)	(8.45)	(3.79)	(2.03)	(3.91)	(2.59)	(1.95)	(26.19)	(6.03)	(0.48)	(12.64)	(4.12)	(0.45)	(0.22)	(3.43)
24	-10.29*	4.67	-1.94	-0.77	1.06	2.44	0.84	-108.06***	26.78***	-2.17***	-95.41***	25.74***	-2.28***	1.15***	-7.46**
	(4.54)	(7.47)	(3.41)	(1.81)	(3.43)	(2.29)	(1.71)	(31.10)	(6.73)	(0.48)	(11.45)	(3.70)	(0.41)	(0.19)	(2.66)

Specification accounts for month-year fixed effects, a CO_2 fee dummy and the price of CO_2 permits. Demand, wind,capacity margin, net imports in GWh. Gas price (PGas) in €/MWh.

Appendix B Robustness check

Table B2 shows the results for a robustness check using time series estimation methods. Here again, we take the difference of the variables from their month-year mean to account for month-year fixed effects and estimate the following regression:

$$P_t = \sum_{h}^{3}[\beta^h L_t^h + \gamma^h W_t^h + \theta^h mar_t^h] + \sum_{j} \zeta^j F_{t-24}^j + \sum_{s} \kappa^s D^s + \chi I_t + \epsilon_t \quad (6)$$

We control for the autocorrelation of the residuals by including lags 1-5 and 22-26 of the residuals, after verifying their autocorrelation and partial-autocorrelation graphs. The marginal effect of wind on system marginal price is equal to -18.33, which is very close to the average of the marginal effects found with the panel estimate (-18.17).

The results of the time series estimates do not disentangle the impact of the wind, the interconnector and the storage during the different hours of the day. The results in Table 3 show that wind generation does not affect the system price homogeneously during the hours. In particular, wind is particularly significant during the night and the first hours of the afternoon, and this effect is not captured in the time series specification. The panel estimation approach also highlights times when the effect of wind is non linear, whereas this effect is masked by the specification used in Equation 6. Finally, storage and interconnector are not significant in Table B2, but Table 3 shows that they are statistically different from zero for several hours of the day.

Table B2: Effect of wind on SMP (€/MWh), hourly data, 2008-2012

Variables	Coeff.
Demand, GWh	167.300***
	(11.312)
$Demand^2$, GWh	-41.403***
	(2.519)
$Demand^2$, GWh	3.625***
	(0.184)
Wind Generation, GWh	-19.756***
	(3.011)
$Wind^2$ GWh	2.11
	(4.565)
$Wind^3$ GWh	0.825
	(1.949)
Gas_{t-24} (€/MWh)	0.414*
	(0.206)
CO_2 (€/tonne)	0.222
	(0.264)
Net Imports, GWh	-23.971***
	(2.19)
Capacity Margin, GWh	-97.157***
	(3.157)
$Cap.Marg.^2$ GWh	24.136***
	(1.303)
$Cap.Marg.^3$ GWh	-1.959***
	(0.168)
TH_{Out}	-1.045
	(1.317)
$Moyle_{Out}$	-4.657
	(2.872)
Wind*TH	-1.898
	(1.321)
Wind*Moyle	1.21
	(1.394)
AR(1)	0.344***
	(0.001)
AR(2)	0.044***
	(0.003)
AR(3)	0.035***
	(0.004)
AR(4)	0.020***
	(0.005)
AR(5)	0.023***
	(0.004)
AR(22)	-0.015***
	(0.004)
AR(23)	0.035***
	(0.003)
AR(24)	0.281***
	(0.002)
AR(25)	-0.077***
	(0.003)
AR(26)	-0.036***
	(0.004)

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1
Includes $CO_2 fee$.

Appendix C Comparison with other studies

Table C3: Percent change in spot price associated with 1MWh change in wind

Paper	Country	Year	Wind share	$\frac{\Delta P}{P}$
Forrest and MacGill (2013)	South Australia	2009-2011	17%	-0.069
	Victoria	2009-2011	2%	-0.027
Nieuwenhout and Brand (2011)	Netherlands	2006-2009	3%	-0.008
Swinand and O'Mahoney (2015)	Ireland	2008-2012	9%	-0.025
Cludius et al. (2014)	Germany	2008	8%	-0.003
		2009	8%	-0.004
		2010	8%	-0.003
		2011	10%	-0.002
		2012	11%	-0.002
Clò et al. (2015)	Italy	2008	2%	-0.011
		2009	2%	-0.011
		2010	2%	-0.008
		2011	2%	-0.008
		2012	4%	-0.006
		2013	5%	-0.005
This paper	Ireland	2008-2012	11%	-0.030
		2008	8%	-0.029
		2009	11%	-0.033
		2010	10%	-0.039
		2011	15%	-0.025
		2012	15%	-0.022

Wind share from Eurostat nrg105a when not available from paper.
% change in price calculated based on data provided in the papers cited.
Forrest and MacGill (2013) truncate the price series to values greater than AUS$1 and smaller than AUS$415. Australia's spot price is real-time price.

Table C3 includes studies that calculate the marginal effect of wind on spot prices. Econometric studies that focus on the average effect of wind, such as Gil et al. (2012) are excluded. The units of measure vary, but we create a common measure that identifies the change in the spot price (in €/MWh) given a 1MWh increase in wind generation. We then calculate the size of that change with respect to the average spot price. This is what we report in the right-most column of Table C3. The average penetration or share of wind is calculated as the share of demand covered by wind generation and comes from each paper when it is reported. For papers that do not report average hourly demand or average hourly wind generation, the average share of wind is calculated using Eurostat data, database nrg105a, and the information on renewables reported in the SHARES tool (`http://ec.europa.eu/eurostat/web/energy/data/shares`). Forrest and MacGill (2013) report penetration for 2011, i.e. the highest point of wind penetration in the dataset. The spot price is the day-ahead price for all jurisdictions except Australia where it is the real-time price.

Appendix D REFIT calculations

We calculate the average cost of REFIT per MWh using half-hourly information on wind generation at the plant level, SMP and capacity payments to generators, downloaded from the market operator's website. We limit the analysis to wind generators in the Republic of Ireland, since REFIT applies only to companies in Ireland.

As stated in the main text, each plant is guaranteed a fixed price that varies by fiscal year, which starts on October 1 and ends on September 30 (shown in Table 6). The payment to wind generators is composed by a fixed portion (15% of the reference price for large wind) and a portion that depends on how much the plants make on the market. The plants receive the SMP and capacity payments from the market (wind generators did not receive constraint payments during this period). The feed in tariff (FIT) amount is calculated every year y for each wind generator i generating electricity $Elec$:

$$FIT_{i,y} = FixFIT_{i,y} + max[P_y^{FIT} - \frac{\sum_{t\in y}(SMP_t + CapPay_{i,t}) \cdot Elec_{i,t}}{\sum_{t\in y} Elec_{i,t}}, 0] \cdot \sum_{t\in y} Elec_{i,t} \quad (7)$$

The first term is the fixed amount and is defined as $0.15 \cdot P_y^{FIT} \cdot \sum_{t\in y} Elec_{i,t}$. The second term shows that a positive REFIT payment is paid only if the generator does not receive at least the REFIT price on its average sales during the year.

Table D4: Summary Statistics on hourly data, 1 January 2008 to 28 August 2012

	Obs.	Mean	Std. Dev.	Min	Max
Large wind (49 plants)					
Generation (MWh)	1,504,160	7.46	9.68	0	85.03
Capacity Payments (€)	1,504,160	52.97	120.18	0	8,146.73
Capacity Payments/MWh	1,342,477	12.34	185.34	0	100,482.00
SMP (€/MWh)	1,504,166	59.40	32.34	0	695.79
Small wind (8 plants)					
Generation (MWh)	192,553	0.73	0.88	0	4.61
Capacity Payments (€)	192,553	5.16	11.16	0	367.18
Capacity Payments/MWh	165,021	12.30	200.99	0	60,110.00
SMP (€/MWh)	192,553	57.70	31.34	0	695.79

Small wind farms have export capacity up to 5MW.

Table D4 summarises the information we have for the 57 wind farms that bid directly into the market during the January 2008 to August 2012 period. The majority of these wind generators (49) are large, while 8 have an export capacity smaller than 5MW. These are much fewer than the total number of wind farms that receive REFIT support, since not all wind plants bid into the SEM. The Electricity Act 2011 lists 118 wind farms with REFIT support, with 71 being large and 47 small.[19] Small wind farms represent about 9%

[19]The Electricity Regulation Act is published in Statutory Instrument No. 513 of 2011.

of total capacity, with large wind farms responsible for the remaining 91%. We implicitly assume that all the small wind farms have a similar generation pattern and the same for large wind farms. In the hourly data for firms registered with the SEM there is one observation where generation is reported as negative and one where capacity payments are negative. We set these observations as missing.

The average REFIT payments by fiscal year and type of wind farm are reported in Table D5. As expected, the average subsidy to small wind farms is larger than to large wind farms. Note that in 2008 there was no variable REFIT paid due to the large SMP. In general, the size of the average REFIT payment is inversely correlated with the SMP. The averages presented in the last two lines are weighted by the number of periods in each year, but not by plant generation in each year.

Table D5: REFIT avg per MWh, by fiscal year, €/MWh

		Large wind		Small wind		
Year	FIT fix	FIT var	Tot. FIT	FIT var	Tot. FIT	SMP
2008	9.56	0	9.56	0	9.56	83.25
2009	9.95	8.28	18.23	11.39	21.34	51.47
2010	9.95	13.56	23.51	15.71	25.66	48.78
2011	9.95	0.84	10.79	2.97	12.92	62.11
2012	10.21	2.09	12.31	5.29	15.50	61.13
Average	9.97	5.14	15.11	7.45	17.49	
Avg from 2009	10.04	4.93	14.96	6.86	16.91	

Data range: 1 January 2008 06:00 to 28 August 2012 23:00.
Fiscal year goes from October 1 of prior year to 30 September.
Average from 2009 is calculated from 1 November 2009.

To calculate the REFIT cost of the average MWh generated by wind under REFIT, we weigh the average REFIT cost by the capacity share of large and small wind farms on the system.

This leads to an average REFIT payment per MWh of $15.11 \cdot 0.91 + 17.49 \cdot 0.09 = 15.32$. To compare to other costs and benefits of wind in our analysis, we also calculate the average REFIT payment for the period starting on November 1 2009, with a value of $14.96 \cdot 0.91 + 16.91 \cdot 0.09 = 15.14$. This is the number that we report as the REFIT cost of 1MWh of wind in the main text.

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