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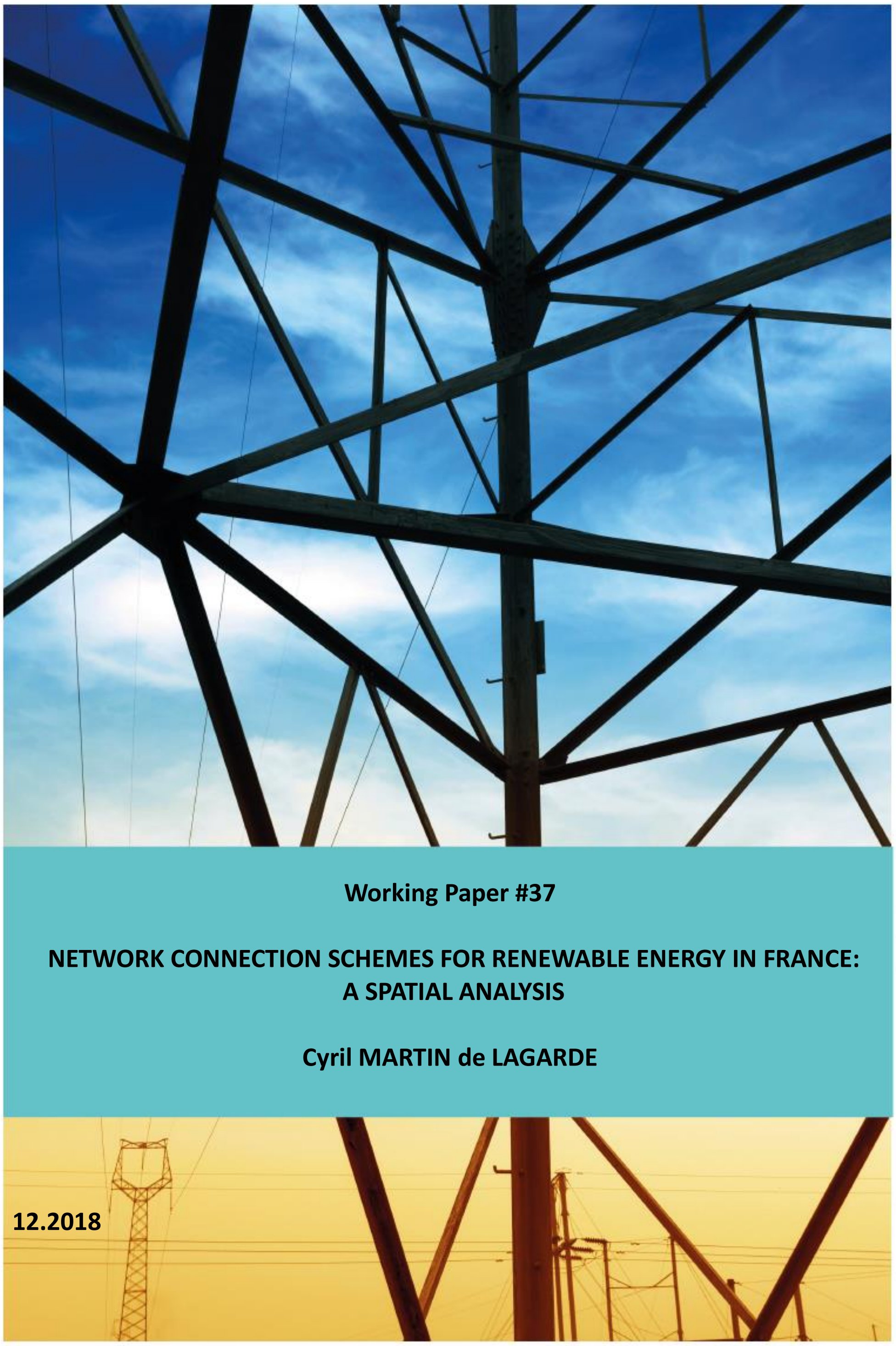
Fondation Paris-Dauphine



Working Paper #37

NETWORK CONNECTION SCHEMES FOR RENEWABLE ENERGY IN FRANCE: A SPATIAL ANALYSIS

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12.2018

DAUPHINE UNIVERSITÉ PARIS

Chaire de recherche soutenue par

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NETWORK CONNECTION SCHEMES FOR RENEWABLE ENERGY IN FRANCE: A SPATIAL ANALYSIS

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December 2018

Abstract

Regional network connection schemes for renewable energy sources (RES) have been set in France in order to avoid "large" (i.e. > 100 kW) RES producers to pay deep-cost connection charges, that were seen as a brake on the development of renewable energy, and to give a locational price signal to RES projects developers. Using a unique database of connection applications by wind producers to the main French DSO's (Enedis) network, we develop a spatial panel model that captures the effect of this innovative regulation as well as spatial dependences of the variables. Thus, we show that the schemes have managed to redirect connection requests towards less constrained regions without altering the global level of connections, and that spatial substitution occurred between regions. On average, an increase of the network charge of €/kW in a region reduces quarterly connection requests by 300 kW in the region while increasing them by 138 kW in the neighbouring ones. Finally, we show that the diffusion of wind energy exhibits an "epidemic" effect, i.e. there is a positive impact of the number of past installations on the number of connection requests.

Keywords: Wind energy; network regulation; connection charges; diffusion; spatial panel models.

Acknowledgments: This paper has benefited from the support of the Chaire European Electricity Markets (CEEM) of the Université Paris-Dauphine under the aegis of the Foundation Paris-Dauphine, supported by RTE, EDF, EPEX Spot and CELEST.

I also wish to thank Enedis for providing the data used in this article, and in particular Christophe Bonnery, François Dispot and Hervé Lextrait. I would also like to thank Anna Creti and Frédéric Lantz for their useful remarks.

Disclaimer: The views and opinions expressed in this paper are those of the authors and do not necessarily reflect those of the partners of the CEEM.

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I. INTRODUCTION

Following the third European energy package, the 2020 "20-20-20" objectives[1] were transposed into French law in August 2009, setting i.a. a target of 23% of renewable energy sources (RES) in the final energy consumption in 2020[2]. This law was completed in July 2010 and an obligation was made for each region to work out a scheme for climate, air and energy (SRCAE[3]), setting regional targets for RES for 2020[4]. Along with these schemes, the transmission and distribution system operators (the TSO - RTE, and DSOs such as Enedis, the DSO for 95% of the population) also had to design a network connection scheme for renewable energy sources for each region. These are named S3REnR or SRRRER[5].

The idea behind this planning tool is to make RES producers share network reinforcement charges, instead of applying the so-called "deep cost" methodology which otherwise prevails in France for electricity production units. This approach charges all network reinforcement costs to the first producer that triggers the reinforcement in question. The resulting uncertainty was considered a barrier to investments in renewable energy projects, which are usually decentralised. They are therefore relatively small compared to centralised units, for which such additional charges weigh less in the total installation cost. On the contrary, RES developers may not afford important network reinforcement charges, so it was decided that they would instead share these costs. Each plant with capacity higher than 100 kW would thus be charged proportionally to its capacity. Note that renewable producers with capacity lower than 100 kW do not pay reinforcement charges at all, and it was even decided that the smallest ones would have their connection subsidised up to 40%. Moreover, regionally differentiated network connection charges were expected to give a locational price signal to RES producers, and hence lead to a more efficient use of the existing network. Higher charges actually mean more network constraints, which should make additional renewable energy production less desirable.

Following the publication of the SRCAE schemes, S3REnRs have been designed by RTE and the DSOs, based on the 2020 targets. In order to meet these targets, they identified a potential RES capacity per electrical substation and computed the associated reinforcement costs. Furthermore, each substation has some capacity (which can be zero) reserved for RES projects, that can be publicly monitored on a dedicated website[6]. When all reserved capacities have been allocated, the scheme is said to be saturated, and another scheme is to be designed and published, with new reserved capacities and asso-

[1] Reduction of 20% of greenhouse gas emissions with respect to 1990, 20% of renewable energy in final energy consumption, and a 20% increase in energy efficiency.

[2] *LOI n^o 2009-967 du 3 août 2009 de programmation relative à la mise en œuvre du Grenelle de l'environnement* [20]

[3] In French: Schémas Régionaux Climat, Air, Énergie, i.e. literally: regional schemes for climate, air and energy.

[4] *LOI n^o 2010-788 du 12 juillet 2010 portant engagement national pour l'environnement* [21]

[5] In French: Schémas Régionaux de Raccordement au Réseau des Énergies Renouvelables, i.e. literally: regional network connection schemes for renewable energy sources.

[6] `https://capareseau.fr/`

ciated network charges. However, nothing is planned in case the target is not met. This issue, among others, has led to some criticisms towards S3REnRs[7]. Thus, the goal of this paper is to assess its efficacy, i.e. whether it provides efficient locational price signals and enhances the development of renewable energy (through the reduction of the uncertainty about network connection charges). Our analysis reveals that this is indeed the case for wind energy, which we have chosen as it is the second RES technology in France (after hydroelectricity). It is also the leading technology being developed, along with solar photovoltaics (PV). The latter is however more difficult to analyse, because of multiple support schemes depending in particular on capacity thresholds and types of installation.

In order to do so, we develop a spatial panel model, whose dependent variable is the number of connection requests of wind farms of more than 100 kW. The model takes into account the spatial autocorrelation of both the dependent and independent variables such as the network connection charge. Since we are dealing with regionally differentiated schemes, we expect RES developers to choose a production site not only based on its production potential (i.e. wind speeds), but also on the value of the network charge. Hence, if a site with a strong potential is located on two or more neighbouring regions, installation is more likely to occur in the "cheapest" one. In other words, we can think of neighbouring regions as substitutes for one another. This is confirmed by our results, as they reveal the existence of negative and significant spatial autocorrelation. This contrasts with previous spatial analyses of RES, that have mainly focused on solar PV, but on a much smaller scale (municipalities or even streets in a city). In these studies, a positive spatial autocorrelation (i.e. a positive influence from the vicinity) was found, which was interpreted as peer effects (see for example [11] for an application to German counties and a review of the literature on PV). Using a unique data set of connection requests provided by Enedis, which we aggregate into 1154 observations of 21 regions over 74 quarters, we show that on average, an increase of the network charge of 1 €/kW in a region reduces quarterly connection requests by 300 kW in the concerned region while increasing them by 138 kW in the neighbouring ones.

Furthermore, the development of wind energy, like other RES, is expected to exhibit an intrinsic diffusion process, as originally described by Bass [5] for durable goods. Thus, we take into account this characteristic, adding an "epidemic" term to the equation. We show that past installations have had a positive and significant impact on the diffusion of wind energy, which is in line with most of the literature on renewable energy. However, we do not observe a "stock" effect yet, which shows that the growth is still on the increase.

Finally, we take into account residual autocorrelation, which is on the contrary found to be positive. This highlights the existence of spatially correlated unobservable variables. These could be wind speeds, as they are positively correlated and undoubtedly have an influence on the choice of location of a wind farm. The remainder of the paper is then organised as follows: section 2 provides a review of the literature, and section 3 presents the data used in our analysis. The spatial panel model is then detailed in section 4, followed by the presentation and discussion of the results in section 5. Section

[7]See for instance the early criticisms of the French Energy Regulator (in French): `http://www.cre.fr/documents/deliberations/avis/energies-renouvelables/consulter-la-deliberation`.

6 concludes the paper.

II. LITERATURE REVIEW

Our article is based on several strands of the literature on RES. The first one is quite general and deals with network regulation and its impact on RES development and spatial location; the second is based on the literature on diffusion, which has widely been applied to RES; the third one studies spatial interactions in RES development.

First of all, few authors have studied the impact of network regulatory rules on the development and spatial location of distributed RES. In a rather qualitative fashion, Anaya and Pollitt [1] analyse regulation and trends in Germany, Denmark and Sweden, focusing on network access and connection charges as well as support mechanisms. They conclude that early support of RES, as in Germany, is a key driver of the their adoption. They also compare connection mechanisms and conclude that the "deep cost" methodology is likely to have a negative impact on the development of RES compared to a "shallow cost" one (in which no reinforcement charges are paid), especially in the case of very high connection charges. Previously, Lopes et al. [22] and Klessmann, Nabe, and Burges [16] had already briefly identified the role of "deep", "shallow", and "shallowish"[8] network connection charges. On a slightly different subject, Brandstätt, Brunekreeft, and Friedrichsen [9] compare the effectiveness of locational energy pricing, locational network pricing, and "smart contracts" in reducing network investments in smart distribution grids. We trust that our research will contribute to this literature by presenting the rather unique French S3REnR network connection schemes and providing quantitative impacts of these schemes.

Secondly, in order to isolate the effect of the S3REnR regulation on wind energy development, it is essential to control for the diffusion process followed by this somewhat new technology. Indeed, several studies have modelled the deployment of electric renewables as following an "S-curve", in the line of the seminal work of Griliches [15], such as Schilling and Esmundo [29] for solar photovoltaics. Others have used diffusion models *à la* Bass [5], mostly to assess the impact of subsidies and/or peer (social) effects on the development of solar photovoltaics (e.g. [8]; [26]). In the case of wind energy, Liu and Wei [19] found that the development of wind power in China has been driven by financial incentives as well as by epidemic effects, using a linear regression equation from a logistic growth function. They follow Benthem, Gillingham, and Sweeney [7], who had previously addressed the subject of subsidies for solar photovoltaics in California in the presence of learning-by-doing. More recently, Baudry and Bonnet [6] used a micro-founded diffusion model to analyse the effectiveness of demand-pull policies on wind energy development in several European countries.

Ultimately, since we are dealing with geographical data, spatial dependence is also likely to occur and hence bias the estimators if not taken into account ([12]). Consequently, several authors have highlighted the existence of spatial dependence, either

[8] Under such charges, only some reinforcement costs are borne by the producer. The French S3REnR schemes could come under this terminology.

when modelling the diffusion processes of RES or when studying their determinants of adoption. For instance, Balta-Ozkan, Yildirim, and Connor [4] analyse the deployment of solar PV in the UK using a cross-section spatial econometrics approach, and find that there are significant regional spillover effects. Spatial panel models have also be used, for example by Graziano and Gillingham [14], who show that adoptions of residential PV in Connecticut (US) have also been driven by neighbouring installations (peer effects), while Müller and Rode [24] previously presented similar evidence in the city of Wiesbaden (Germany) using a spatial panel logit model. More recently, Dharshing [11] performed a spatial panel econometrics study on the dynamics of adoption of residential solar panels in Germany. In all these studies, spatial spillovers are positive and are then interpreted as peer effects at the local level. To the best of our knowledge however, no one has investigated the presence of spatial dependence in the case of wind power yet. Wind power being usually much more capital intensive than small-scale PV, there are fewer projects than PV ones. As a consequence, higher spatial aggregation is required, so that positive spillovers are likely to be "diluted" and hence be absent at this scale. On the contrary, we will show that spatial autocorrelation is negative as a result of substitution in the choice of a location, but that there exist positive residual autocorrelation. Our model thus constitutes a rare example among spatial econometric models, whilst keeping an intuitive interpretation[9].

III. DATA

In order to perform our analysis, we use publicly available dates of enforcement and shares of connection charges for of all 21 regional schemes, as well as connection requests data provided by Enedis for wind farms with a capacity higher than 36 kW, from January 1998 to June 2016.

3.1. Network connection charges

On the one hand, we used publicly available data on S3REnRs. The documents relative to these network connection schemes are published on the RTE's website[10]. The corresponding documents contain a lot of information: a description of the regional network and its evolution, how the scheme was prepared and realised, which reinforcements have been selected and how much they cost, how much reserved capacity[11] there is per substation, etc. They are published along with other documents, such as public consultation reports, technical and financial status, transfer[12] or saturation[13] notifications.

[9] As noted by Anselin and Bera [2]: "Of the two types of spatial autocorrelation, positive autocorrelation is by far the more intuitive. Negative spatial autocorrelation implies a checkerboard pattern of values and does not always have a meaningful substantive interpretation".

[10] `https://www.rte-france.com/fr/article/les-schemas-regionaux-de-raccordement-au-reseau-des-energies-renouvelables-des-outils` (in French).

[11] The schemes are based on a regional target for RES capacity, which is then subdivided in "reserved capacities" for each substation, that cannot be used for non-RES projects.

[12] Reserved capacity at a substation can be "transferred" to another substation within the same scheme, provided the global capacity and the network charge remain unchanged. This allows some flexibility in the scheme, if all substations are not used as originally planned.

[13] When all reserved capacity has been allocated to RES projects, the scheme is said to be saturated, and a new scheme is to be designed and published. Until then, the network charge remains unchanged.

All this information can be very useful to RES project developers in particular. For the purpose of our study however, we are only interested in the date of enforcement of the scheme, and the related network charge, in €/kW, and their possible changes (only one region - Champagne-Ardenne, has been concerned with a change so far, as a saturation was anticipated[14]).

Figure 1 below shows the variation of the network charge per region, and table 1 presents some descriptive statistics. We have used the first value of the charge in Champagne-Ardenne, which rose from 49.26 to 53.17€/kW at the end of 2015. From these can be seen that network charges are rather heterogeneous, although six regions (out of twenty-one) have a charge almost equal to 10€/kW, and eleven have a charge "concentrated" between 9€/kW and 20€/kW only. The aforementioned features appear clearly on the whole data set (A.1) or the histogram (figure A.1) in appendix 1. Nevertheless, eight values are relatively spread between 20 and 70€/kW.

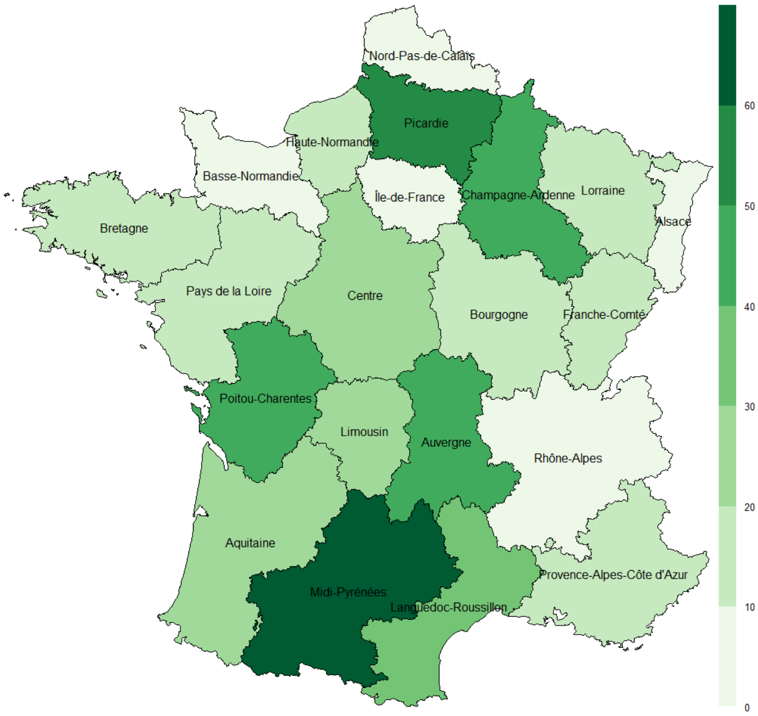


Figure 1 – Network reinforcement charges per region (€/kW), before revision.

Min	Q1	Med.	Mean	Q3	Max	S.D.
0	10.11	18.21	23.72	35.63	69.90	19.40

Table 1 – Descriptive statistics of regional network reinforcement charges (€/kW), before revision

In addition, these charges can be compared with the other driving costs of a wind farm project. As an indication, CRE [10] and SER [30] give a cost magnitude of about

So far only two regions - Picardie and Nord-Pas-de-Calais, have their scheme saturated, but no revision has been published yet.

[14] See the new scheme ([27]).

1000€/kW for wind turbines, which represent roughly 75% of total costs. Although the network reinforcement charges are very small compared to the cost of the turbine, we need to remember that wind farms have been subsidised thanks to feed-in tariffs, which have now been replaced by feed-in premiums. These subsidies aim at giving an "adequate" return on investment to project developers. As a result, they take into account the capital and operating costs, but not the regional charges, or at least not on a per-region basis. Consequently, we can still expect these to have an impact on the location choice of wind farms.

Dates of enforcement are also quite heterogeneous in time, and it took more than three years to have all schemes came into effect. In order to have enough data per period, we chose to aggregate it at the quarterly time step. This keeps the heterogeneity of dates of enforcement, as at most four schemes came into force during the same quarter (Q4 2012). As they have not particularly been enforced at the beginning or end of a quarter, we consider that the share of reinforcement costs was still equal to zero during the quarter of implementation, and we control this simplification by adding a dummy variable for the quarter in question. This dummy is also a measure of the effectiveness of the scheme. In particular, we expect it to have a lower coefficient than the post-enforcement dummy, since it captures the effect of the reform for less than a quarter.

3.2. Network connection requests

On the other hand, we used data provided by Enedis, the distribution system operator (DSO) for 95% of French customers. More precisely, we have information on the date at which they entered the "waiting list", which makes them eligible for the applicable feed-in tariff and liable for the network charge. We also have details on their location (city) and capacity.

After a request is addressed to the network operator, it has three months to send back a technical and financial proposition, which is then valid for three months. When the proposition is accepted, the project enters the waiting list, for which it stays on average for 782 days. However, about 35% of projects are abandoned and withdrawn from the waiting list without being connected, in which case the mean stay in the waiting list is still of 427 days. If on the contrary the connection is completed, it is of 1010 days, and the longest connection project took 4409 days (12 years).

Thus, due to the long delay between the connection request and the actual connection or the abandonment of the project, it is impossible to study the number of requests that effectively led to a connection without removing a large part of the sample. Even doing so, we would remove projects that may have led to a connection in the future. We have thereupon decided to focus on connection requests, which nonetheless give a good proxy of the future number of wind farms (one could still assume a constant rate of abandonment). They are also responsible for the lengthening of the waiting list and hence for the possible saturation of the schemes and the triggering of network reinforcements.

This data is quite relevant for the analysis of the regional schemes, since up to mid-2016 (which is when our data set finishes) 89% of wind capacity has been connected to Enedis' network, and 71% of the wind-energy waiting list is on Enedis' network as well. It increases mainly on its network too ([28]). This can be explained by the fact that the capacity limit between the distribution and the transmission networks is equal to 12 MW for production units, with a possible extension up to 17 MW, while the average size of a wind farm was 15.3 MW in 2016 ([13]). Furthermore, bigger wind farms tend to ask for several connections to the distribution network rather than one connection to the transmission network. This can be seen by looking at the number of connection requests that occur the same day in the same city. Indeed, we have 20.3% of "multiple connections", which are mostly "double connections" (16.6%). The comparison of statistics in table 2 and 3 below also highlights this fact. However, aggregated request can only be used as a proxy for the study of multiple connections, since some wind farms are connected to substations in different cities, and sometimes at different dates. This probably leads to an underestimation of this phenomenon. On the contrary, there could be several connection requests in the same city at the same date for distinct projects, but this seems very unlikely. A more rigorous analysis would require a long and thorough examination of the data set and would be beyond the scope of this study.

Unfortunately, we do not have connection requests data from RTE, nor from the other small DS0s (approximately 5% of DSOs' customers). However, the number of connections on RTE's network is rather limited, and the use of regional fixed effects should control for the presence of some relatively large DSOs in some regions. Moreover, we have 78 out of 2388 connection requests for which we do not have the location. This accounts for 3.4% of the data in terms of number of observations as well as connection capacity.

Single requests	12	10	8	11,5	6	9,2	4	9	6,9	2
N	410	285	143	124	77	72	59	49	47	38
Aggregated requests	12	10	8	11,5	6	4	16	13,8	24	9,2
N	255	171	101	77	61	40	37	34	32	30

Table 2 – Ten most frequent capacities for single and aggregated (city-day) connection requests (MW)

	N	Min	Q1	Med.	Q3	Max	Mean	St. dev.
Single requests	2308	106	7500	10000	12000	17000	9225	3564
Aggregated requests	1837	106	8000	11000	13800	99750	11590	7561

Table 3 – Descriptive statistics for single and aggregated (city-day) connection requests (kW)

Since we use connection requests for wind projects of more than 100 kW, i.e. those concerned by the network charge, there could be some "down-sizing" behaviour for wind projects just above 100 kW to avoid paying the network charge. However, projects under 100 kW represent only 0.002% of total capacities (and 0.75% of the number of connection requests), and are therefore negligible. This is confirmed by the non-truncated histogram of connection requests capacities in figure 2, which also highlights the 12 MW and 17 MW limits[15]. The histogram also reveals the fact that most wind farms probably

[15]We have removed two "outliers" at 152.300 MW and 64.580 MW, which correspond to abandoned

rely on 2 MW-turbines, which is also confirmed by table 2, as most frequent connection requests are multiples of 2 MW.

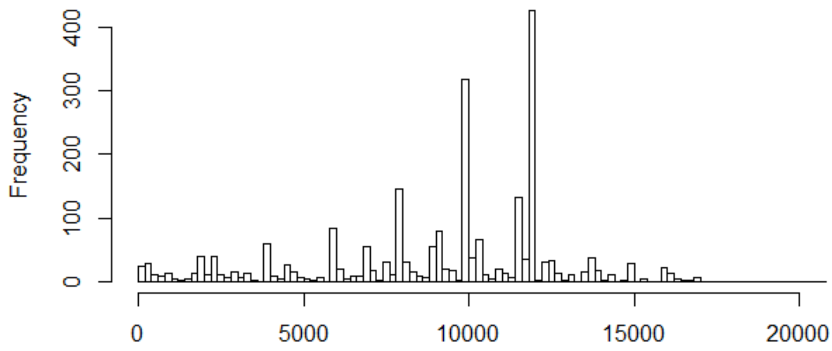


Figure 2 – Histogram of connection requests capacities (kW)

Figure 3 displays the temporal evolution of quarterly demand for wind projects of more than 100 kW on Enedis' network. It is clear from this graph that the dynamic is very different from one region to another, as some regions have no wind farm at all (Aquitaine) or almost none (e.g. Alsace and Provence-Alpes-Côte d'Azur). On the contrary, Picardie and Champagne-Ardenne (and to a lesser extent Nord-Pas-de-Calais) are the most advanced regions in terms of installed wind capacity, as can be seen on figure 6 and 5 in the next subsection. This explains why the scheme in Picardie is already saturated and the ones in Champagne-Ardenne and Nord-Pas-de-Calais have been revised.

Figure 4 helps visualise the actual heterogeneity between regions, as it displays the quarterly mean demand for wind farms with a 95% confidence interval. We see that the confidence interval can be up to twice as large as the mean, which is the sign of a very strong inter-regional dispersion.

3.3. Installed base

Following the work of Bass [5], we will use the installed base, i.e. the cumulative connected capacity in a given quarter, as an indicator of diffusion. Indeed, the development of wind energy is expected to follow an intrinsic diffusion process, which needs to be controlled for. However, it would not be relevant to compute the installed base from cumulative demands as is usually the case, for the reasons we have just mentioned (delays and abandonment of projects). Furthermore, as pointed out by Narayanan and Nair [25], the use of the cumulative stock of the dependent variable in a panel regression gives biased and inconsistent estimators because it introduces a covariate which is serially correlated with the dependent variable. They advocate the use of an instrumental variable, which can be very difficult to find, or a bias-correction approach, which requires no error autocorrelation.

Noting this issue, Bollinger and Gillingham [8] show in the case of solar panels that if the lag between the adoption decision and the installation is sufficiently large (with

wind farm projects. It is not clear why such big projects were in the DSO's register instead of the TSO's one.

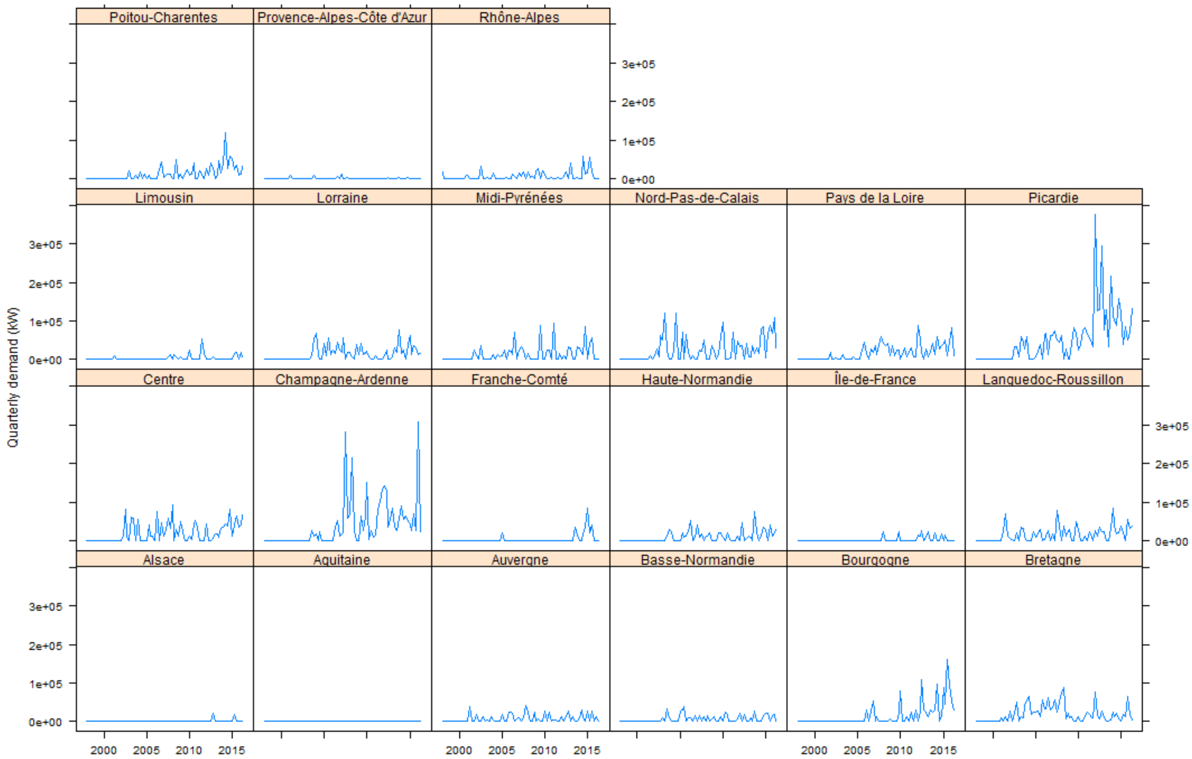


Figure 3 – Quarterly demand for wind projects of more than 100 kW

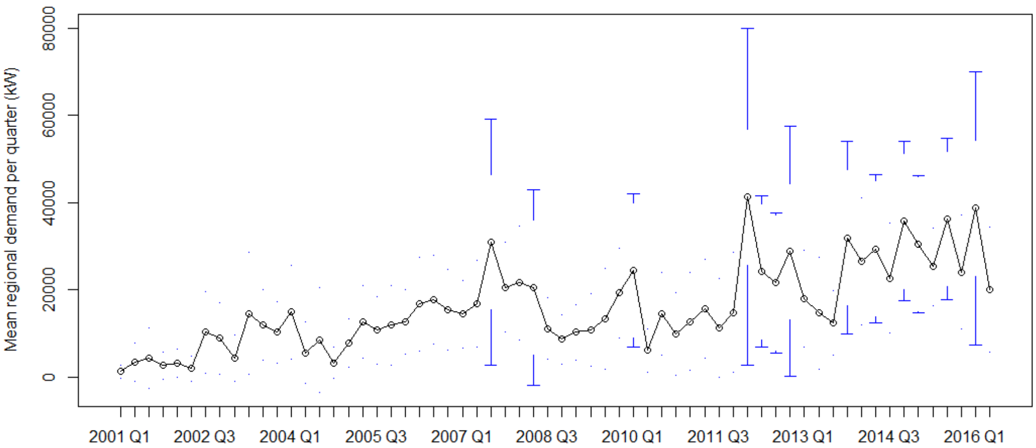


Figure 4 – Heterogeneity of connection requests between regions

respect to the order of autocorrelation of errors), then the estimators are consistent and unbiased. This is particularly suitable for our study, because of the very long delay between the request and the actual connection. Figure 5 and 6 below display the evolution of the installed base per region and their geographical distribution at the end of June 2016. It can be noted that it is highly heterogeneous, which is a direct consequence of the heterogeneity of connection requests. Also, figure 5 shows that most diffusion curves do not have the shape of an S yet, so that we can consider the technology to still be at a fairly early stage. In particular, this excludes the use of the squared installed base as a diffusion variable, which usually aims at capturing the "stock" effect, i.e. the saturation of the market.

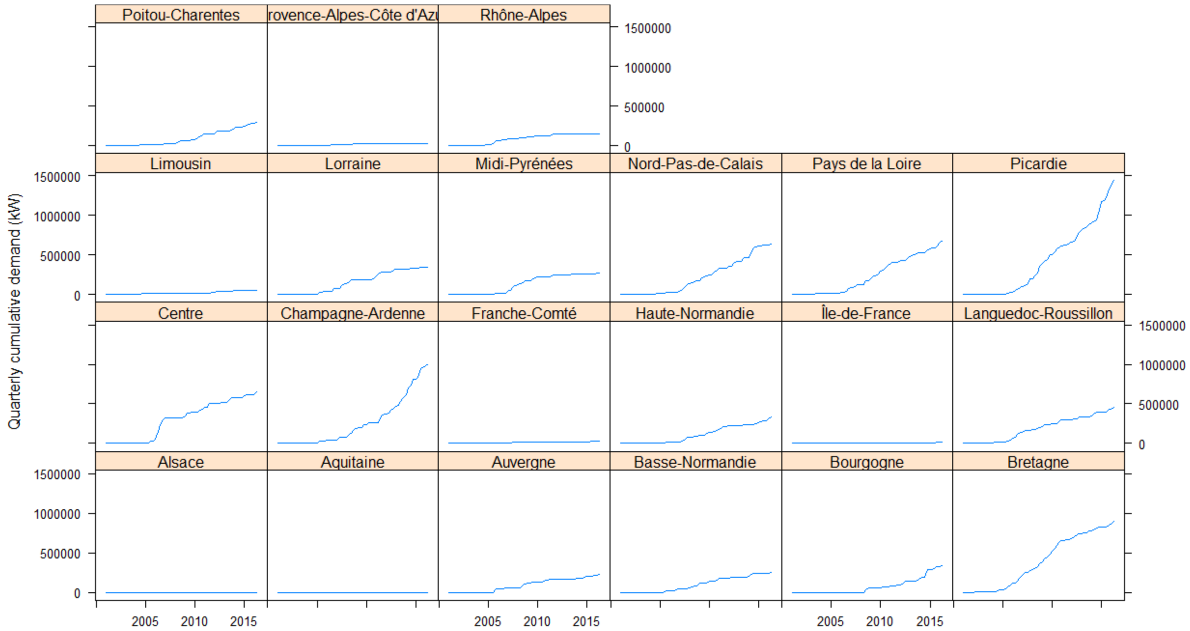


Figure 5 – Installed based per region

IV. MODELLING STRATEGY

Assessing the impact of the S3REnR charge on wind energy deployment requires to consider the data set as a panel, despite the strong observed heterogeneity between regions. Indeed, independent regressions could not give us an estimate of this effect. At best we could get an average value of the impact of the scheme per region, for example using a difference-in-differences approach. However, this would ignore the intensity of the reinforcement charge, which can vary widely across regions. Ergo, we develop a panel data model with region and time fixed effects in order to capture as much heterogeneity as possible. The data being geographical, we also take spatial interactions into account, as explained in the following subsection.

4.1. Spatial interactions

Since we are dealing with geographical data, it is necessary to investigate possible spatial autocorrelation of the variables in order to avoid having biased and inconsistent estimators. In particular, spatial interaction can be present in the three following forms.

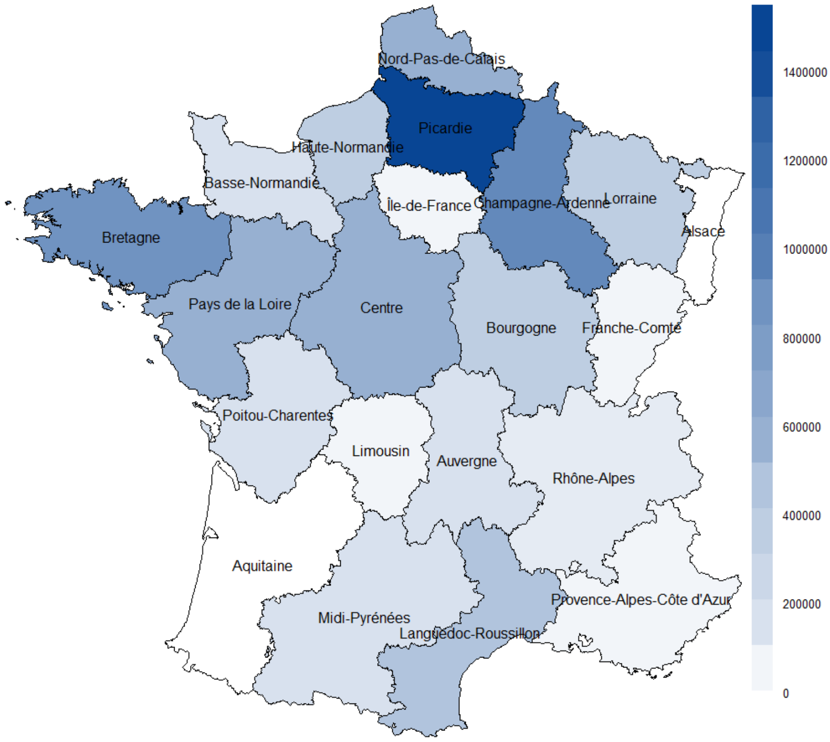
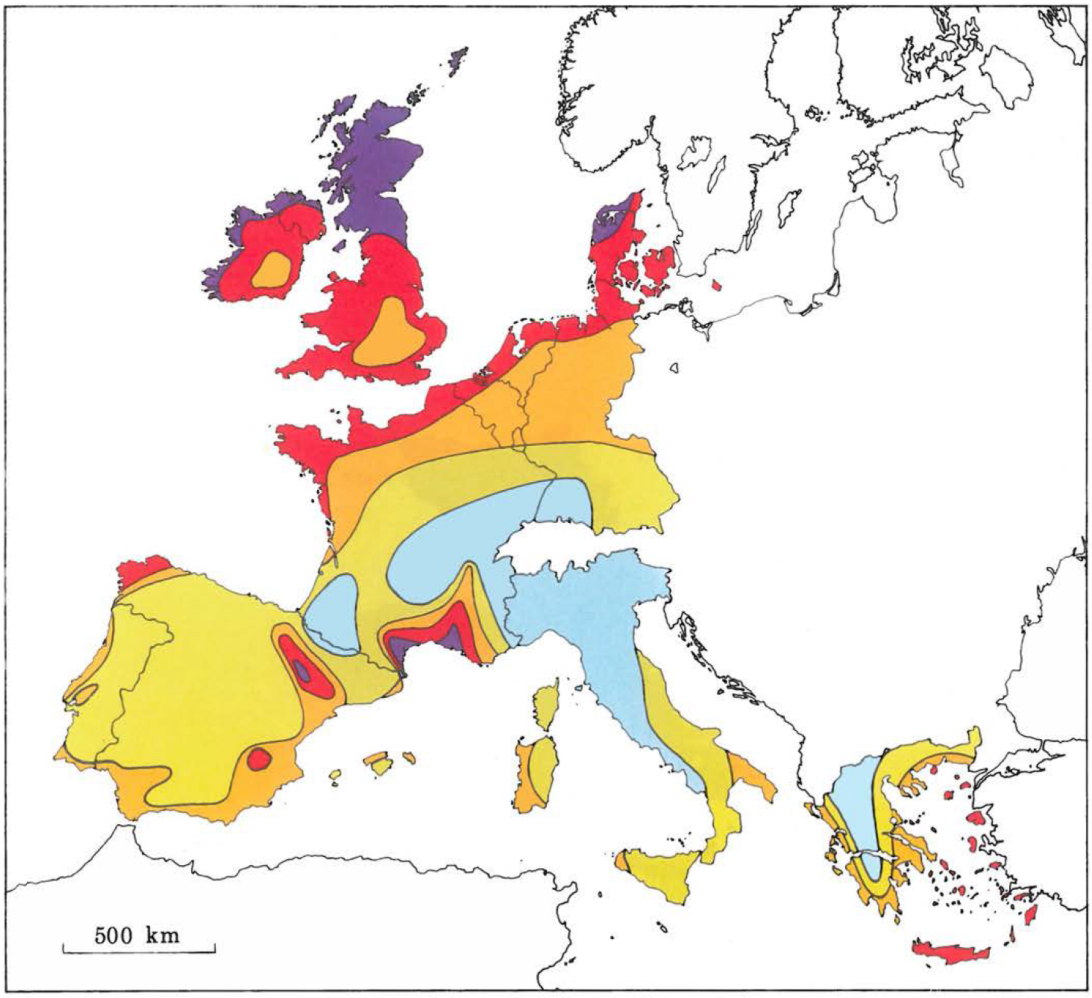


Figure 6 – Regional cumulative wind capacities (kW) connected to Enedis' network, mid-2016

First of all, it can be endogenous, when the outcome in a region impacts the outcome in a neighbouring one, for example as a consequence of peer effects or substitution, as described in section 1. Spatial interaction may also be exogenous, when it comes from the covariates, i.e. if a variable change in a region has an effect in the neighbouring ones. This could be the case for network connection charges. Thirdly, there can be a residual spatial interaction, when spatially correlated unobservable variables affect the dependent variable. For instance, wind speeds are expected to be a rather influential factor in the location choice of a wind farm, and they are spatially autocorrelated (positively), as can be seen from figure 7. In France, winds are strongest on the Channel and Atlantic coasts, as well as on the Mediterranean coast. Wind corridors such as the Rhône valley in the southeast also exist.

Although wind is not unobservable strictly speaking, it is difficult to integrate it as an explanatory variable for several reasons. Firstly, there is no simple relationship between wind speeds and wind energy potential. It is in general nonlinear and dependent on the technology used. Secondly, even if this relationship was known, wind speeds (and hence potential output) can vary within a single region. In this case, a unique indicator will not capture the diversity of wind regimes within a same region. For example, one could use the maximum, mean or median value, or other statistic, but there is no obvious choice. Finally, the use of a single-valued (i.e. non-panel) covariate per region would prevent us from using individual fixed effects, that provide the means to capture other unobservable variables as well.



	Wind resources[1] at 50 metres above ground level for five different topographic conditions									
	Sheltered terrain[2]		Open plain[3]		At a sea coast[4]		Open sea[5]		Hills and ridges[6]	
	m s^{-1}	Wm^{-2}	m s^{-1}	Wm^{-2}	m s^{-1}	Wm^{-2}	m s^{-1}	Wm^{-2}	m s^{-1}	Wm^{-2}
	> 6.0	> 250	> 7.5	> 500	> 8.5	> 700	> 9.0	> 800	> 11.5	> 1800
	5.0-6.0	150-250	6.5-7.5	300-500	7.0-8.5	400-700	8.0-9.0	600-800	10.0-11.5	1200-1800
	4.5-5.0	100-150	5.5-6.5	200-300	6.0-7.0	250-400	7.0-8.0	400-600	8.5-10.0	700-1200
	3.5-4.5	50-100	4.5-5.5	100-200	5.0-6.0	150-250	5.5-7.0	200-400	7.0-8.5	400-700
	< 3.5	< 50	< 4.5	< 100	< 5.0	< 150	< 5.5	< 200	< 7.0	< 400

Figure 7 – Wind speeds in Europe. Source: Troen and Lundtang Petersen [31].

4.2. Spatial panel model

In order to take spatial interactions into account, one needs to define a vicinity relationship between the $N = 21$ regions under study. In spatial econometrics, the relationship takes the form of a $N \times N$ symmetric matrix W, whose coefficients w_{ij} (weights) describe the vicinity relationship between regions i and j, and are usually distance or contiguity-based. Distance-based coefficients can be useful for instance in "gravity-like" models and have the advantage of being parameterised in relatively "simple" spatial models. In our case, we find it more relevant to use a contiguity-based matrix, as is often the case in spatial econometrics. In particular, we use a first-order contiguity-based matrix, whose weights w_{ij} are equal to 1 if regions i and j are considered as neighbours, and 0 otherwise[16]. More precisely, we use a rook-style weight matrix, were regions that share a common edge are considered as neighbours[17], as represented by the graph in figure 8. This choice is frequent in spatial econometrics, and quite natural for our study, since we are interested in possible substitution between neighbouring regions. Indeed, the potential location of a wind farm is not likely to extend over non-contiguous regions, as exploration of potential sites can be relatively costly for wind energy companies.

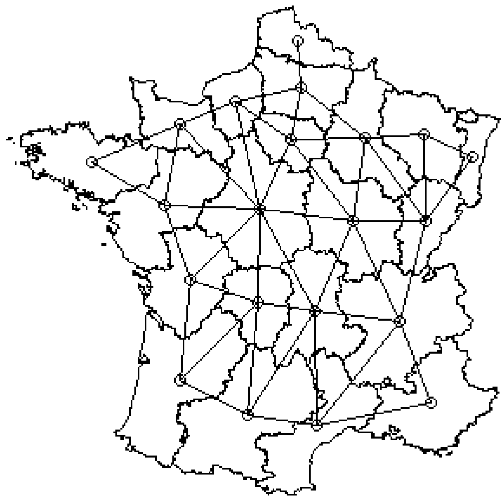


Figure 8 – Graph of rook neighbours

As a consequence of all possible spatial interactions described in the previous subsection, we choose to model connection requests capacity using the following general nesting spatial (GNS) panel model with space and time fixed effects:

$$\begin{cases} S = \rho(\mathbb{1}_T \otimes W_N)S + X\beta + (\mathbb{1}_T \otimes W_N)X\theta + (\iota_T \otimes \nu) + (\delta \otimes \iota_N) + u \\ u = \lambda(\mathbb{1}_T \otimes W_N)u + \varepsilon \end{cases} \tag{1}$$

where W_N is the $N \times N$ row-standardised weight matrix[18], $\otimes$ denotes the Kronecker (or tensor) product and $\mathbb{1}_T$ is the identity matrix of dimension T, so that $\mathbb{1}_T \otimes W_N$ is an

[16] $w_{ii} = 0$, i.e. a region is not considered to be its own neighbour.

[17] A similar possibility, the queen-style weight matrix, considers that regions that share a common edge or corner are neighbours. In our case, this would lead to the exact same matrix as the rook-style one.

[18] The matrix is standardised so that the sum of the terms in each row is equal to 1 (or zero if a region has no neighbour)

$NT \times NT$ block matrix whose diagonal elements are T W_N matrices. The dependent variable S is represented in stacked form as a $NT \times 1$ vector, as well as the error terms ε and u. Independent variables X are stacked in a $NT \times K$ matrix, where K is the number of covariates. The parameters to be estimated are hence: ρ and λ, the spatial autoregressive and spatial error coefficients; β and θ, the coefficients of covariates and spatially lagged ones, of length K; ν, a vector of individual fixed effects of length N; δ, a vector of time fixed effects of length T, and ι_N (resp. ι_T) is a vector of length N (resp. T) filled with ones. Moreover, it is assumed that the idiosyncratic error vector ε verifies: $\mathbb{E}[\varepsilon] = 0$ and $\mathbb{E}[\varepsilon\varepsilon'] = \sigma^2 \mathbb{1}_{NT}$, and is identically and independently distributed. Additionally, regional and time fixed effects verify $\nu'\iota_n = 0$ and $\delta'\iota_T = 0$. For simplicity, the model can be rewritten in the following "instantaneous" form, omitting the N subscript for the weight matrix:

$$\begin{cases} S_t = \rho W S_t + X_t\beta + W X_t\theta + \nu + \delta_t\iota_N + u_t \\ u_t = \lambda W u_t + \varepsilon_t \\ \varepsilon_t \rightsquigarrow IID(0, \sigma^2) \end{cases} \tag{2}$$

where S_t, u_t and ε_t are vectors of length N, and X_t is a $N \times K$ matrix.

So, the GNS model contains the three types of spatial interactions described above: endogenous (ρ), exogenous (θ) and residual (λ). However, it has been criticised for often giving non-significant estimates ([12]), and it is thus rarely used in spatial econometrics. Researchers usually use several restrictions of the GNS model, which are similar to time series models (in their denomination). If covariates are only considered locally (i.e. when $\theta = 0$), we have a spatial autoregressive combined (SAC), or spatial autoregressive errors (SARAR) model. If in addition $\lambda = 0$ it is called a spatial autoregressive (SAR) model, and if on the contrary $\rho = 0$ it is a spatial error (SEM), or spatial moving average (SMA) one. A less frequent kind of model is the spatial cross regressive, or spatial lag independent variables (SLX) one where only $\theta \neq 0$. Finally, a SAR (resp. SEM) with spatially lagged covariates is called a spatial Durbin (error) model (SD(E)M).

Elhorst [12] recommends using the two latter, but warns that "both models tend to produce spillover effects that are comparable to each other in terms of magnitude and significance, and because interaction effects among the dependent variable on the one hand and interaction effects among the error terms on the other hand are only weakly identified. Precisely for this reason, the general nesting spatial (GNS) model is not of much help either. It generally leads to a model that is overparameterized, as a result of which the significance levels of the variables tend to go down." (p.33). In our case, all spatial interactions are justified from an economic and physical (in the case of wind speeds) point of view. Consequently, we have decided to keep the GNS model, whose estimates are almost all statistically significant, as we will show in the next section.

Finally, the independent variables in X are: the installed base Y defined earlier, the regional S3REnR charge T (which is considered to be zero up to the quarter of enforcement t_i, included), a dummy variable for when the regional scheme is enforced, and a dummy variable equal to 1 afterwards. The use to these two dummy variables takes into account the fact that the enforcement does not usually happen at the beginning or end of a quarter. Furthermore, the enforcement quarter dummy aims at capturing a possible "deadline" effect, i.e. a possible "rush" before the enforcement, in order to avoid paying the network charge.

V. RESULTS AND INTERPRETATION

5.1. Estimation results and first interpretations

We estimate the model 2 over the whole sample ($T = 74$ and $N = 21$) using the R package **splm** developed by Millo and Piras [23]. The main estimation results are displayed in table 4 below, while time and region fixed effects can be found in appendix 2. The R-squared is $R^2 = 0.308879$, which is an "acceptable" value (although not of much interest) for panel models, and the results are robust when considering time lags of the installed base a well as a SAC specification.

	Estimate	Std. Error	t-value	p-value
ρ	-0.4272	0.1090	-3.92	0.0001
λ	0.3277	0.0902	3.63	0.0003
Y	0.0415	0.0051	8.17	0.0000
$W \times Y$	-0.0068	0.0093	-0.73	0.4628
T	-285.8	92.85	-3.08	0.0021
$W \times T$	-363.2	177.6	-2.04	0.0409
$\mathbb{1}[t > t_i]$	7,579	4,297	1.76	0.0778
$W \times \mathbb{1}[t > t_i]$	10,801	9,283	1.16	0.2446
$\mathbb{1}[t = t_i]$	12,904	5,395	2.39	0.0168
$W \times \mathbb{1}[t = t_i]$	20,676	11,069	1.87	0.0618

Table 4 – Estimation results of the GNS panel model

Because of the endogenous spatial correlation, we cannot readily interpret the numerical value of all these coefficients (see next subsections). Nonetheless, we can do so for the spatial autocorrelation parameters ρ and λ. First of all, they are both highly significant. Secondly, the former is negative, contrarily to what has been observed for residential solar panels. So, we do not observe peer effects, but rather some substitutability between regions: the more connection requests in a given region, the less connection requests in the neighbouring ones. In a way, a negative ρ can be interpreted as the "marginal rate of substitution" between two neighbouring regions, all other things held constant. This could have several explanations, the most simple of which is the existence of arbitrage when the choice of a region is to be made. Indeed, as the number of "large" wind energy projects is rather limited[19], the location choice of a wind farm in a region may come at the expense of a neighbouring but as promising one (all other things being equal). On the contrary, the residual autocorrelation coefficient λ is positive. This may reflect the autocorrelation of wind speeds, as described in the previous section, but other unobservable variables such as population or income may also be spatially correlated (although not necessarily at such a large scale).

Finally, we see that ρ and λ are well identified. This may be due to the fact that they have

[19] In comparison, the number of small-scale PV projects is very large, so that the market could almost be considered as atomistic.

opposite signs, whereas negative spatial autocorrelation seems to be pretty rare elsewhere in spatial econometrics, which probably makes the two coefficients less identifiable. In particular, results are relatively robust under the other specifications described above, unless the estimates of ρ and λ when one of them is set to zero. Indeed, in that case it can be hard to determine whether spatial interaction is endogenous or residual. Ergo, the estimation of one of the two parameters when the other is zero gives an "average" value of the two, which in our case is roughly equal to -0.1. In the SAC (SARAR) specification however, both estimates are very close to the ones of the GNS model.

5.2. Interpreting coefficients: simplified example

Similarly to autoregressive models in time series, the coefficients of spatially autoregressive models cannot be interpreted directly[20]. To see this, let us first consider a simplified SDM model with only two neighbouring regions and one covariate X. For the sake of simplicity, we do not write the error term, as it plays no role in the computation of the marginal effects. Thus, we have the two following equations:

$$\begin{cases} S_{1t} = \alpha_1 + \beta X_{1t} + \theta X_{2t} + \rho S_{2t} \\ S_{2t} = \alpha_2 + \beta X_{2t} + \theta X_{1t} + \rho S_{1t} \end{cases} \tag{3}$$

which can be solved for example either by substituting variables in the two equations, or computing the inverse of the matrix $\mathbb{1} - \rho W$. Solving the system leads to:

$$\begin{cases} S_{1t} = \dfrac{\alpha_1 + \rho\alpha_2}{1-\rho^2} + \dfrac{\beta + \rho\theta}{1-\rho^2} X_{1t} + \dfrac{\theta + \rho\beta}{1-\rho^2} X_{2t} \\ S_{2t} = \dfrac{\alpha_2 + \rho\alpha_1}{1-\rho^2} + \dfrac{\beta + \rho\theta}{1-\rho^2} X_{2t} + \dfrac{\theta + \rho\beta}{1-\rho^2} X_{1t} \end{cases} \tag{4}$$

From this simple resolution it is clear that demands in both regions are interrelated, and that a change in X_i will have both a (direct) impact on S_i, with a sign equal to $\beta + \rho\theta$'s sign, and an (indirect) impact on S_j ($i \neq j$), with a sign equal to $\theta + \rho\beta$'s sign. When $theta = 0$, the direct impact is "amplified" by $\dfrac{1}{1-\rho^2} > 1$. This is a result of "feedback", i.e. the fact that a region is a neighbour of its neighbours, and is impacted by even powers of ρW accordingly.

From equation 3, we see that if $\rho > 0$, an increase of the dependent variable in a region increases it also in the neighbouring one, i.e. there is a complementarity effect. If on the contrary $\rho < 0$, there is a substitution effects. Furthermore, if $\rho > 0$ and $|\theta|$ is "small enough" compared to $|beta|$ (or if θ and β have the same sign), then the direct and indirect marginal effects of X have the same sign, so that the regions are indeed complements with respect to the variable X. Conversely, if $\rho < 0$ and $|\theta|$ is "small enough" (or if θ has the sign of $-\beta$), they have opposite signs, and the regions are indeed substitutes. In our case for example, a higher S3REnR charge in a given region is expected to decrease the number of connection requests within this region, but a higher charge in neighbouring regions is expected to increase it if substitution between region is possible.

[20] If there is no spatial autocorrelation, i.e. if $\rho = 0$, the interpretation of the coefficients is the same as in an OLS regression. This is the case in particular for SEM, SDEM and SLX models.

Finally, it is also interesting to write the gradient of $S = (S_1, S_2)$ with respect to $X = (X_1, X_2)$, as this representation will be use in the next subsection for the general case:

$$\frac{\mathrm{d}S}{\mathrm{d}X} = \begin{pmatrix} \frac{\partial S1}{\partial X1} & \frac{\partial S1}{\partial X2} \\ \frac{\partial S2}{\partial X1} & \frac{\partial S2}{\partial X2} \end{pmatrix} = \begin{pmatrix} \frac{\beta+\rho\theta}{1-\rho^2} & \frac{\theta+\rho\beta}{1-\rho^2} \\ \frac{\theta+\rho\beta}{1-\rho^2} & \frac{\beta+\rho\theta}{1-\rho^2} \end{pmatrix} \tag{5}$$

The diagonal terms are therefore the marginal effects of covariates X_1 and X_2 on S_1 and S_2, respectively. The off-diagonal terms are the marginal impacts of X_2 (resp. X_1) on S_1 (resp. S_2).

5.3. Interpreting coefficients: general case

More generally, equation 2 can be rewritten:

$$S_t = (\mathbb{1} - \rho W)^{-1}(X_t\beta + WX_t\theta + \nu + \delta_t\iota_N + u_t) \tag{6}$$

Using the Taylor expansion of the inverse matrix: $(\mathbb{1} - \rho W)^{-1} = \mathbb{1} + \rho W + \rho^2 W^2 + ...$, we see that in fact an infinite number of spatially lagged values of the covariates and of the error term appear in the equation for S, corresponding to neighbours of neighbours, etc. Also, as $|\rho| < 1$, the closest neighbours have the most influence. LeSage and Pace [17] suggest that the marginal effect be decomposed into a direct effect and an indirect (or spillover) effect, the sum of which is the total effect (which can only be considered when the change in a covariate occurs globally and identically). Indeed, we can write the marginal effects of the r$^{\text{th}}$ covariate on the dependent variable as the following $N \times N$ matrix, which is the generalisation of equation 5:

$$\frac{\partial S}{\partial x_r'} = (\mathbb{1} - \rho W)^{-1}(\mathbb{1}_N\beta_r + W\theta_r) \tag{7}$$

As in the simplified case, the partial derivative at line i and column j quantifies how an infinitesimal change of covariate r in region j impacts S in region i. In particular, the diagonal terms represent the direct marginal effects and off-diagonal elements the indirect ones. From there, we can compute average direct, indirect and total marginal effects, the latter being the sum of the two former ones[21].

Finally, measures of dispersion of the estimated direct, indirect and total marginal effects are also needed for inference. Indeed, due to their computation, nothing can be said for these from the standard deviations and levels of significance of the "raw" estimates. Again, we follow LeSage and Pace [17], who suggest to produce empirical distributions of the parameters "using a large number of simulated parameters drawn from the multivariate normal distribution of the parameters implied by the maximum likelihood estimates" (p.39). LeSage and Pace [18] then suggest to use medians as point estimates and scaled median absolute deviations (MAD) as measures of dispersion, which are more robust to outliers and distribution asymmetry than the sample mean and standard deviation.

[21] In SDEM and SLX models, (in)direct effects are simply the coefficients of the (spatially lagged) covariates, since there is no endogenous spatial autocorrelation.

5.4. Direct, indirect and total marginal effects

Table 5 below shows the simulated direct, indirect and total marginal effects, along with p-values, levels of significance, and 95% confidence intervals, as recommended e.g. by Armstrong [3]. These are based on 10,000 simulations realised using a personal program written in R.

	Direct	Indirect	Total
Y (kW/kW)	0.0435***	-0.0132***	0.0302***
	(2×10^{-16})	(3×10^{-4})	(6×10^{-12})
	[0.0344;0.0524]	[-0.0f195;-0.0077]	[0.0230;0.0375]
T (€/kW/kW)	-300***	138***	-155**
	(0.002)	(0.010)	(0.033)
	[-460;-137]	[61;239]	[-279;-39]
$\mathbb{1}[t > t_i]$ (kW)	7,855*	-3,717	3,915
	(0.082)	(0.105)	(0.209)
	[484;15,457]	[-8,063;-420]	[-1,093;9,178]
$\mathbb{1}[t = t_i]$ (kW)	13,497**	-6,726**	6,394*
	(0.018)	(0.036)	(0.091)
	[4,381;22,866]	[-12,786;-2,268]	[480;13,064]

Note: p-values are in parentheses.
Asterisks denote significance levels of 99% (***), 95% (**), and 90% (*).
95% confidence intervals are in brackets.

Table 5 – Direct, indirect and total marginal effects of the GNS model

As expected, the direct and total marginal effects have the sign of the coefficients of the non-lagged variables in table 4, and the indirect ones have the opposite sign. The direct marginal effects are higher, which is a consequence of the "feedback", but the increase is more than compensated by the indirect effects, so that the total effects are smaller than the non-lagged estimates. This illustrates the difficulty to interpret the "raw" estimates. Only the post-enforcement quarter dummy has little significance, especially in its total marginal effect.

Concerning the installed base, we see that on average, an additional MW in a region increases the quarterly requests by 43.5 kW, and an additional MW in each region leads to an increase of 30.2 kW. These values may seem small but can nevertheless lead to an important increase in the long run, as long as there is no "stock" effect.

An increase of the network charge in a region T of 1€/kW reduces the connection requests by 300 kW and increases it by 138 kW in neighbouring regions, as a consequence of substitution. These values are quite significant and relatively high, which shows that the schemes have sent appropriate locational signals. For instance, the inter-quartile difference of network charges is equal to 25.52€/kW, which means a (direct effect) difference of 7,656 kW in quarterly connection requests, while the mean capacity request is equal to 9,225 kW (see table 3). In the short run, the implementation of the schemes have had a positive impact on the connection requests, which may be due to a "deadline" effect. On average, 6,394 additional kW have been installed in each region due to the enforcement of the schemes. In the long run, the impact would be of 3,915 kW/quarter, although this estimate is not very significant (contrarily to the direct impact).

Finally, table 6 below displays the overall direct, indirect and total effects of the network charge plus scheme enforcement per region (i.e. $\beta_T \times T + \beta_{\mathbb{1}[t>t_i]}$). We see that the direct and total impacts are positive in 15 out of 21 regions, and negative in 6. Thus, the positive effect of the schemes compensates the negative one of the network charge in most regions. On average, the schemes have only slightly increased the quarterly demand for wind projects, and are consequently almost neutral regarding the capacity requests at the national level. Nevertheless, they have led to a more efficient (in the sense of network constraints) spatial distribution of these requests, which was one of the goals of this regulation. Although these values do not reflect the exact reality, since they have been computed using statistical estimates, it is interesting to analyse them by looking at neighbouring regions. For instance in the South, the Rhône-Alpes region may have benefited from a rather low network charge while its neighbours Auvergne and Languedoc-Roussillon were negatively affected. Similarly, in the North, Nord-Pas-de-Calais and Haute-Normandie may have benefited from a low charge as well as from a high charge in the neighbouring Picardie. Looking at the map of connected wind farms in appendix 3, we can see that there exist several wind farms close to the borders of these regions. This makes the above explanations quite plausible. In addition, substitution may also occur on a larger scale than just across the borders, depending on how large potential sites are.

Region	Charge (€/kW)	Direct	Indirect	Total
Alsace	0	7,855	-3,717	3,915
Aquitaine	23.37	843	-441	300
Auvergne	48.4	-6,657	2,948	-3,587
Basse-Normandie	9.81	4,911	-2,334	2,384
Bourgogne	16.92	2,829	-1,353	1,245
Bretagne	10.11	4,840	-2,270	2,303
Centre	20	1,822	-876	784
Champagne-Ardenne	49.26	-6,876	3,077	-3,794
Franche-Comté	10.64	4,671	-2,217	2,235
Haute-Normandie	10.19	4,837	-2,271	2,297
Île-de-France	1.5	7,418	-3,503	3,685
Languedoc-Roussillon	35.63	-2,807	1,232	-1,628
Limousin	22.56	1,073	-534	383
Lorraine	18.21	2,373	-1,184	1,002
Midi-Pyrénées	69.9	-13,022	5,944	-6,936
Nord-Pas-de-Calais	9.19	5,156	-2,417	2,501
Pays de la Loire	13.38	3,889	-1,805	1,812
Picardie	58.6	-9,722	4,343	-5,163
Poitou-Charentes	42.36	-4,734	2,158	-2,667
Provence-Alpes-Côte d'Azur	18.48	2,358	-1,111	998
Rhône-Alpes	9.51	5,002	-2,364	2,460
Average	23.7	765	-414	216

Table 6 – Expected regional effects of the regional connection schemes (kW/quarter)

VI. CONCLUSIONS AND POLICY IMPLICATIONS

We have shown that regional network connection schemes for renewable energy have had a significant impact on the diffusion of wind energy. This relatively unique regulation consists in a per-kW fee that aims at sharing network reinforcement costs among RES producers of more than 100 kW. This charge is differentiated between regions, which enhances locational arbitrage opportunities when adjacent regions have distinct charges or when only some of them have implemented their scheme. This substitution can be seen through the study of spatial autocorrelation, which is found to be negative, as is the impact of the network charge. The regulatory framework also aims at removing the uncertainty on connection charges due to the deep-cost methodology that prevails in France, and we show that this is indeed the case, as the overall effect is almost neutral on average and positive for most regions.

Moreover, we have shown that the cumulative installed capacity has had a positive and significant impact on connection requests. This highlights the "epidemic" behaviour of the diffusion process, which is sometimes neglected in the assessment of renewable energy policies. Similarly, spatial interactions are often forgotten in econometric studies. This is unfortunate, as their omission usually gives biased and inconsistent estimators. Hence, we hope that our positive results will encourage more econometricians to use spatial models in the future.

In the end, the conclusive results of the French regulation could lead other countries to use similar schemes to help promote renewable energy and planning its development by taking the existing network constraints into account. This may avoid or delay unnecessary and costly network reinforcements, if these are charged in a "reasonable" way to the producers. However, the French schemes also have some drawbacks. For example, once the regional target is attained, another target and a new scheme have to be defined. On the contrary, if the target is never met, or not in time, some producers may have payed for unnecessary reinforcements. Also, although the choice of proportional charges is easy to understand and may seem rather natural, one could think of other cost-sharing methodologies, as discussed in the cooperative game theory literature. Finally, one could also challenge the choice of the regional scale for such schemes. Indeed, transmission and distribution networks may differ in topology within the same region, hence leading to potential inefficiencies. Despite their imperfections, these schemes remain quite innovative in a highly regulated energy sector, and have proven to have achieved their goals.

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APPENDICES

A. REGIONAL CONNECTION SCHEMES DATA

Region	Enforcement date (d/m/y)	Enforcement quarter	Network reinforcement charge (€/kW)
Alsace	21/12/2012	2012 Q4	0
Aquitaine	15/04/2015	2015 Q2	23.37
Auvergne	28/02/2013	2013 Q2	48.40
Basse-Normandie	16/09/2014	2014 Q3	9.81
Bourgogne	21/12/2012	2012 Q4	16.92
Bretagne	07/08/2015	2015 Q3	10.11
Centre	20/06/2013	2013 Q2	20.00
Champagne-Ardenne	27/12/2012	2012 Q4	49.26
Champagne-Ardenne (modified)	29/12/2015	2015 Q4	53.17
Franche-Comté	12/09/2014	2014 Q3	10.64
Haute-Normandie	24/10/2014	2014 Q4	10.19
Île-de-France	04/03/2015	2015 Q1	1.50
Languedoc-Roussillon	08/01/2015	2015 Q1	35.63
Limousin	16/12/2014	2014 Q4	22.56
Lorraine	18/11/2013	2013 Q4	18.21
Midi-Pyrénées	08/02/2013	2013 Q1	69.90
Nord-Pas-de-Calais	21/01/2014	2014 Q1	9.19
Pays de la Loire	13/11/2015	2015 Q4	13.38
Picardie	26/12/2012	2012 Q4	58.60
Poitou-Charentes	07/08/2015	2015 Q3	42.36
Provence-Alpes-Côte d'Azur	26/11/2014	2014 Q4	18.48
Rhône-Alpes	15/01/2016	2016 Q1	9.51

Table A.1 – Regional connection schemes data set

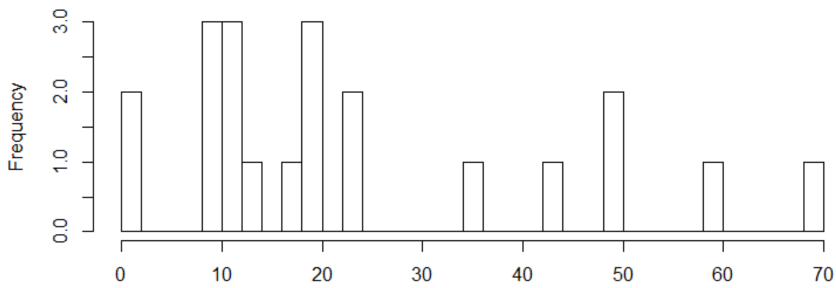

Figure A.1 – Histogram of network connection charges (€/kW

B. FIXED EFFECTS OF THE GNS PANEL MODEL

	Estimate	Std. Error	t-value	p-value
Intercept	13658.83	1260.89	10.83	0.00

Quarter	Estimate	Std. Error	t-value	p-value
1998 Q1	-12331.80	4553.97	-2.71	0.01
1998 Q2	-13658.83	4553.97	-3.00	0.00
1998 Q3	-13658.83	4553.97	-3.00	0.00
1998 Q4	-13658.83	4553.97	-3.00	0.00
1999 Q1	-13658.83	4553.97	-3.00	0.00
1999 Q2	-13658.83	4553.97	-3.00	0.00
1999 Q3	-13658.83	4553.97	-3.00	0.00
1999 Q4	-13658.83	4553.97	-3.00	0.00
2000 Q1	-13658.83	4553.97	-3.00	0.00
2000 Q2	-13658.83	4553.97	-3.00	0.00
2000 Q3	-13658.83	4553.97	-3.00	0.00
2000 Q4	-13128.02	4553.97	-2.88	0.00
2001 Q1	-11918.91	4553.97	-2.62	0.01
2001 Q2	-8555.58	4553.97	-1.88	0.06
2001 Q3	-7574.03	4553.97	-1.66	0.10
2001 Q4	-9838.71	4553.97	-2.16	0.03
2002 Q1	-9300.38	4553.97	-2.04	0.04
2002 Q2	-11126.08	4553.97	-2.44	0.01
2002 Q3	2467.16	4553.97	0.54	0.59
2002 Q4	-1776.35	4553.98	-0.39	0.70
2003 Q1	-8289.61	4553.98	-1.82	0.07
2003 Q2	6835.43	4553.99	1.50	0.13
2003 Q3	4561.22	4554.01	1.00	0.32
2003 Q4	717.88	4554.01	0.16	0.87
2004 Q1	8378.78	4554.01	1.84	0.07
2004 Q2	-6821.93	4554.01	-1.50	0.13
2004 Q3	-3484.94	4554.05	-0.77	0.44
2004 Q4	-9374.52	4554.12	-2.06	0.04
2005 Q1	-2611.69	4554.12	-0.57	0.57

Quarter	Estimate	Std. Error	t-value	p-value
2005 Q2	3659.75	4554.38	0.80	0.42
2005 Q3	1909.55	4555.15	0.42	0.68
2005 Q4	1297.88	4556.71	0.28	0.78
2006 Q1	3634.68	4558.26	0.80	0.43
2006 Q2	10894.41	4561.85	2.39	0.02
2006 Q3	9654.99	4568.95	2.11	0.03
2006 Q4	7826.10	4577.97	1.71	0.09
2007 Q1	5428.56	4583.60	1.18	0.24
2007 Q2	8456.60	4589.26	1.84	0.07
2007 Q3	29937.95	4598.13	6.51	0.00
2007 Q4	13056.49	4609.32	2.83	0.00
2008 Q1	15856.06	4611.44	3.44	0.00
2008 Q2	12157.34	4622.11	2.63	0.01
2008 Q3	-834.86	4642.85	-0.18	0.86
2008 Q4	-6099.02	4663.67	-1.31	0.19
2009 Q1	-3122.99	4682.30	-0.67	0.50
2009 Q2	-2061.68	4702.77	-0.44	0.66
2009 Q3	1039.38	4711.72	0.22	0.83
2009 Q4	8727.06	4736.49	1.84	0.07
2010 Q1	4279.41	4747.98	0.90	0.37
2010 Q2	-10401.89	4765.46	-2.18	0.03
2010 Q3	2439.00	4785.30	0.51	0.61
2010 Q4	-4456.64	4811.45	-0.93	0.35
2011 Q1	-1557.99	4834.10	-0.32	0.75
2011 Q2	1335.07	4845.17	0.28	0.78
2011 Q3	-4266.10	4874.41	-0.88	0.38
2011 Q4	-158.52	4888.69	-0.03	0.97
2012 Q1	42373.60	4898.91	8.65	0.00
2012 Q2	14026.62	4915.77	2.85	0.00
2012 Q3	10855.68	4943.71	2.20	0.03
2012 Q4	14988.78	5498.87	2.73	0.01
2013 Q1	-3516.84	5296.05	-0.66	0.51
2013 Q2	-5803.78	5442.14	-1.07	0.29
2013 Q3	-2984.61	5494.88	-0.54	0.59
2013 Q4	19814.30	5606.59	3.53	0.00
2014 Q1	8328.60	5708.62	1.46	0.14
2014 Q2	17568.97	5751.89	3.05	0.00
2014 Q3	-2703.37	6113.82	-0.44	0.66
2014 Q4	8235.28	6664.42	1.24	0.22
2015 Q1	4414.29	7156.27	0.62	0.54
2015 Q2	-1122.16	7447.25	-0.15	0.88
2015 Q3	9859.11	7782.28	1.27	0.21
2015 Q4	-4378.45	8100.20	-0.54	0.59
2016 Q1	-3238.09	8431.23	-0.38	0.70
2016 Q2	-5588.10	8636.01	-0.65	0.52

Table B.1 – Time fixed effects

Quarter	Estimate	Std. Error	t-value	p-value
Alsace	-11740.60	2705.85	-4.34	0.00
Aquitaine	-9183.25	2545.21	-3.61	0.00
Auvergne	-2771.48	2715.80	-1.02	0.31
Basse-Normandie	-3274.91	2936.67	-1.12	0.26
Bourgogne	3871.00	2685.84	1.44	0.15
Bretagne	-2751.45	2938.84	-0.94	0.35
Centre	-8.61	2819.01	-0.00	1.00
Champagne-Ardenne	11433.49	2843.67	4.02	0.00
Franche-Comté	-8299.50	2709.97	-3.06	0.00
Haute-Normandie	-622.24	2794.20	-0.22	0.82
Île-de-France	-377.90	2930.52	-0.13	0.90
Languedoc-Roussillon	-2847.65	2655.58	-1.07	0.28
Limousin	-6071.56	2622.98	-2.31	0.02
Lorraine	-1345.37	2759.56	-0.49	0.63
Midi-Pyrénées	-3204.37	2675.93	-1.20	0.23
Nord-Pas-de-Calais	20745.83	3439.32	6.03	0.00
Pays de la Loire	2202.55	2841.97	0.78	0.44
Picardie	29915.83	3043.46	9.83	0.00
Poitou-Charentes	436.21	2624.18	0.17	0.87
Provence-Alpes-Côte d'Azur	-9101.09	2590.67	-3.51	0.00
Rhône-Alpes	-7004.94	2592.32	-2.70	0.01

Table B.2 – Region fixed effects

C. MAP OF CONNECTED WIND FARMS

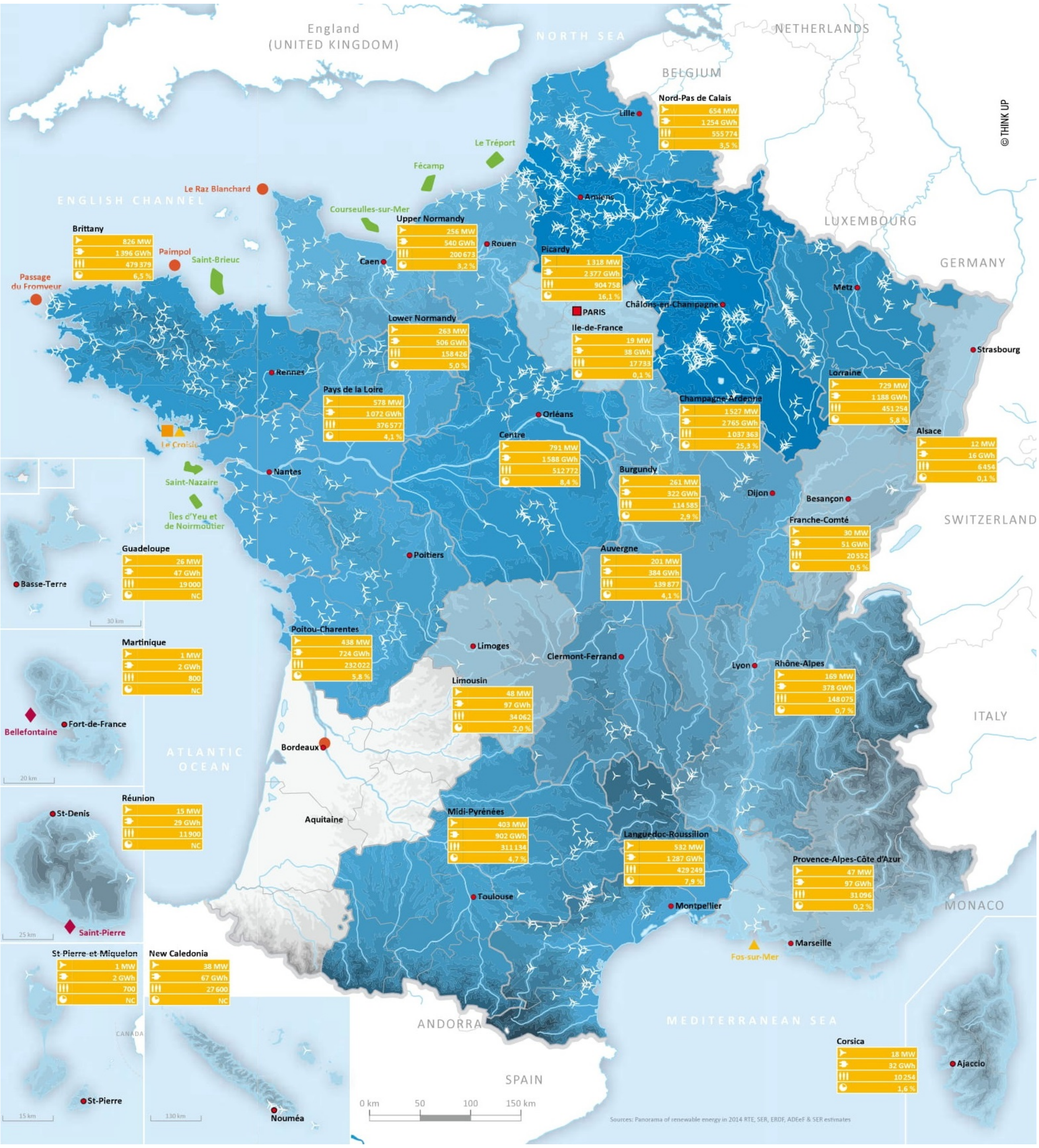

Figure C.1 – Map of wind connected wind farms on January 1st, 2015. Source: Windustry France [32]. Note: Values of connected capacity do not match our data exactly as we only have connections on Enedis' network.