Renewable energy drivers in France: a spatial econometric perspective
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ABSTRACT
This article presents an empirical investigation of factors influencing local renewable energy (RE) deployment. The existing literature has mainly focused on the global contribution of RE at the macro-country level. The particularity of this study resides in the extension of the analysis to the local level, and it was motivated by the fact that the targets for RE deployment are partly defined at the national level, but the establishment of the means of production and the organization is delegated to the local level. Using French data for 95 administrative divisions (départements), we estimate a spatial panel data econometric model by considering serial correlation in the remainder errors. The results reveal strong spatial spillovers and high time persistence, suggesting that the presence of proximity between French local governments conducts local RE policies. The RE deployment of a given department is thus affected by its neighbours. Some determinants of RE deployment are finally identified to help authorities to increase RE supply in the future. Income effect is significant and derived for solar energy and bioenergy and is supplemented by indebtedness that seems to be a favourable strategy to increase solar RE investments. Political ideology is likely to partly explain wind and bioenergy deployment. Finally, geographical factors remain important drivers: solar energy is more developed in southern regions while wind power is more deployed in the north. Based on these results, policy coordination between departments is required to maximize their natural potentialities and increase RE deployment in the future.

KEYWORDS
renewable energy; spatial spillovers; serial correlation; spatial autoregressive (SAR) model; wind; solar; bioenergy

JEL C23, O20, Q42, Q43

INTRODUCTION

Renewable energy (RE) is developing at a remarkable rate throughout the world, and especially in some European countries. First, this development is driven by increasing energy demand: in France, for example, primary energy consumption changed from 1692.26 kg oil-equivalent per capita in 1960 to 3689.52 kg in 2015. Second, the increasing deployment of RE is explained by the rising cost of fossil fuels and the goal of reducing greenhouse gas (GHG) emissions in order to achieve the Paris Climate Agreement. It is indeed urgent to substitute fossil fuels energy consumption by RE since the energy demand is still mostly satisfied by fossil fuels (coal, oil, natural gas) would have negative effects on the environment through CO$_2$ emissions (Apergis & Payne, 2009; Soytas et al., 2007).

Anthropogenic GHG emissions have increased since the pre–industrial era, mainly due to economic and population growth, leading to atmospheric concentrations of CO$_2$, methane (CH$_4$) and nitrogen oxide (NO) (Pachauri et al., 2014). Despite the increasing number of climate change mitigation policies, total anthropogenic GHG emissions continue to increase and reached 49 Gt in 2010, an increase of 81.5% between 1970 and 2010 (Figure 1). A significant part (about 78% of the total increase in GHG emissions between 1970 and 2010) of these emissions is attributable to fossil fuels and industrial processes. In this context, the challenge is how to produce the energy needed to meet world consumption by reducing negative externalities on the environment? This question covers many issues – both environmental and socio-economic – that concern the promotion and development of...
RE (wind power, hydropower, solar energy, biomass, etc.). Consequently, strategies to increase the contribution of RE to the total energy supply are on the agenda in most countries. In this respect, the European Union (EU) has set several targets that aim to develop a greener society and promote a low-carbon economy by 2050.

The success of the agreement critically depends on the implementation of climate policies at the national level (Roelfsema et al., 2020). EU countries are committed to achieving their own national RE targets, ranging from 10% for Malta to 49% for Sweden, with France having set a target of 23% for 2020 (RED, 2009/28/EC). In France, RE accounted for 10.9% of the energy package in 2016 compared with 5.9% in 2006, corresponding to a 5-point increase. However, the RE deployment is heterogeneous across French regions (Figure 2).

The spatial heterogeneity observed in the local RE production can be attributed to specific factors that must be identified in order to design appropriate policies for RE deployment in the future. While the RE production targets for 2020 have been defined at the national level, the establishment of the means of production has been

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**Figure 1.** Global CO₂ emission, economic growth and energy mix. Source: Dong et al. (2018).

**Figure 2.** Average annual growth of renewable energy (RE) production, 2008–16. Source: Authors’ own calculations.
largely delegated to the local level, with significant involvement of the local authorities in the promotion of new technologies (MEEDM, 2009). The energy transition law for green growth (LTECV\(^2\)) has strengthened the competence of local authorities in the fight against climate change through the regional scheme for climate, air and energy (SRCAE\(^3\)). Indeed, the quantitative and qualitative targets for RE production are defined in the SRCAE. Each region has an obligation to make this plan in which it defines its objective. These plans are managed by the prefect of the region and the regional councils in order to identify the potentials of region and define the objectives to contribute to national and European objectives in terms of energy consumption reduction and related GHG emissions, RE production, air quality and climate change adaptation. The territorial plan for climate–air–energy (PCAET\(^4\)) territorializes the SRCAE and implements its guidance in terms of air quality, energy and climate. It is compulsory for all inter-communality with own taxation of more than 20,000 inhabitants across its territory, and must be compatible with the SRCAE. Regarding to the connection network, the LTECV assigns to the electricity transmission network operator (RTE), in agreement with the distribution network operator ENDIS (which operates 95% of the electricity distribution network), the design of the network connection scheme for RE sources for each region (S3REN). The national government supports and regulates local government initiatives to promote RE deployment. The support provided is both financial (subsidies, tax reductions, research and development (R&D) funding\(^5\)) and technical, with assistance provided by agencies (Agence de la transition écologique (ADEME), the agency for energy and ecological transition, etc.). Policy mechanisms are also implemented to accelerate investment in RE technologies such as the feed-in tariff (FIT) and the renewable portfolio standards (RPS) in the United States. The RPS use quota regulation to stimulate investment in RE, while the FIT is a means of price regulation by giving incentives to producers (Jenner et al., 2012).

The purpose of this article is not to compare these policies, but to provide decision-makers with levers they can use to define and justify appropriate RE development policies. We propose to investigate why certain French areas are more RE deployment oriented than others. In other words, what are the determinants of local RE deployment? We aim to identify specific local characteristics that influence a department’s RE deployment, including local internal factors such as socio-economic or environmental factors, geophysical conditions, and political considerations. The influence and magnitude of effects related to geographical proximity are also considered in order to evaluate inter-departmental spatial spillovers.

The existing literature has mainly focused on the global contribution of RE at the macro-country level (Marques et al., 2010), the share of RE in gross energy consumption (Cadoret & Padovano, 2016), and global RE production (Bird et al., 2005) or on the natural logarithm of the share of RE in total electricity generation (Carley, 2009; Damette & Marques, 2019). The RE development level in a given local administrative area (region, department) differs from one sector to another and depends on maturity (which is accompanied by lower cost). Indeed, the RE deployment is a multi-actor system with potential contradictory incentives between active and passive actors, between national and local governments, and between local governments themselves. The local governments accompany and organize the decision-making process previously initiated at a country level (Michalena & Angeon, 2009).

Consequently, several studies have focused on a micro-economic approach for residential solar diffusion (Schaffer & Brun, 2015, in Germany; Balta-Ozkan et al., 2015, in the UK; and Mildenberger et al., 2019, in the United States). For France, Lagarde (2018) uses discrete-choice models and investigates the impact of financial incentives (FIT and local subsidies) on residential photovoltaic (PV) diffusion. However, the availability of solar energy varies according to both location and time (weather conditions and time of day/season) (Balta-Ozkan et al., 2015). Indeed, RE is strongly linked to certain natural resources (sun, wind, land availability) that are distributed in space in different proportions, leading to intermittency problems. Therefore, physical proximity could lead to resource allocation similarities. In addition, innovative activity is more likely to occur in close geographical proximity to the source of that specific knowledge (Audretsch & Feldman, 1996).

Recently, Horbach and Rammer (2018) revealed substantial regional differences in RE innovation across the federal states of Germany due to localization advantages, positive agglomeration effects and resource push effects. Fadly and Fontes (2019) explain that domestic adoption of RE technologies is likely to be affected by the adoption pattern in neighboring countries, especially when they are important trade partners. Shahnazi and Shabani (2020) identify spatial spillovers of RE production due to the mechanism of knowledge diffusion, learning and imitation of neighbouring countries’ policies.

Thus, we go the way of this emerging literature about technology proximity by considering the importance of localization in the RE deployment policy between local governments. It is reasonable to believe that the level of solar, wind and bioenergy development for a given region can be affected by neighbouring regions, and vice versa. If RE deployment policies are partly defined at the national level, their implementation is delegated to the local level. In addition, resources are distributed throughout the territory, but at different levels, therefore understanding local factors that drive RE deployment would be likely optimize the production of RE. Our study is part of this logic. It focuses on the French department level (NUTS-3). Indeed, we collect data for about the 94 French departments over the period 2009–17 to study the RE deployment at a local level.\(^6\)

In this way, spatial dependence must be taken into account when analysing RE deployment, which explains the need to consider the spatial econometrics. Spatial panel models can control for both heterogeneity and spatial correlation (Balagi et al., 2003), but static versions
of these models generally preserve the presence of serial correlation in the spatial econometrics literature (Baltagi et al., 2007). In our case, following Baltagi et al. (2007) and Millo (2014), we decided to use a spatial panel framework in which serial correlation is considered in the remainder errors in order to analyse the determinants of RE at a local level (French departments) considering potential spillover effects.

The remainder of the paper is structured as follows. The next section presents the related empirical literature. The third section examines the spatial distribution of RE in France. The fourth section presents the potential determinants of RE deployment. The econometric framework is presented in the fifth section, before the results in the sixth section. After some robustness checks, the last section concludes.

EMPIRICAL SURVEY

RE deployment is attracting considerable attention worldwide. The growing interest in these alternative energy sources stems mainly from their ability to satisfy the needs of societies in terms of economic investment by simultaneously improving energy security and by reducing pollution related to the energy sector. Therefore, it is essential to develop a sound understanding of this type of energy and of the drivers that should be used to promote its deployment. In this way, several authors have focused on the RE determinants at a macro-economic level.

Menz and Vachon (2006) were probably the first to examine the drivers of RE deployment by analysing the contribution of wind power development in several US state-level policies, in particular the RPS. The results suggest that development of wind energy capacity in a given state depends not only on a state’s natural wind resource endowment, but also on particular policies adopted by state governments to promote wind power. Consequently, the RE deployment is the result of a combination of physical and political factors. Carley (2009) extends this analysis by focusing on 50 US states between 1998 and 2006 using a fixed effects vector decomposition (FEVD), which is more robust than the ordinary least squares (OLS) estimation previously used by Menz and Vachon (2006). As in Menz and Vachon (2006), the RPS is associated with an increase in wind energy deployment and gross domestic product (GDP). The impact of GDP on RE deployment has been the subject of several discussions in the literature, but no consensus has been achieved. Some other macroeconomic studies based on econometric regression methodology show that higher income leads to greater investment in RE deployment, hence economic factors are also crucial drivers in decisions to increase RE production (Aguirre & Ibikunle, 2014; Damette & Marques, 2019; Omri & Nguyen, 2014; Polzin et al., 2015). However, Marques et al. (2010), Marques and Fuinhas (2011), Cadoret and Padovano (2016) and Romano et al. (2017) report a negative effect of GDP on RE development, suggesting that certain highly developed countries have not sufficiently invested sufficiently in RE power. These controversial results may reflect some endogeneity issues due to missing variables problems. RE deployment also poses major challenges for manufacturing industries, especially those operating in the energy sector, and in fossil fuels in particular. This has prompted petroleum industry lobbies to exert pressure to maintain their market shares. This factor is well identified by Marques et al. (2010), Cadoret and Padovano (2016) and Jenner et al. (2012). However, environmentalists and the green energy industry are also exerting pressure to increase RE deployment, as reported by Cadoret and Padovano (2016).

Marques et al. (2010), using panel data regression – in particular the FEVD – analyse for the first time the explanatory factors for RE deployment in European countries from 1990 to 2006. The results of this study show that pressure from lobbies, efforts at improving energy security, CO2 emissions and revenues are important factors in RE deployment in European countries. In this vein, the analysis of the effect of political factors on the deployment of RE sources by Cadoret and Padovano (2016) shows that lobbying in the manufacturing industry effectively delays RE deployment, while standard measurements of the quality of governance outline a positive effect.

At worldwide level, Pfeiffer and Mulder (2013) study the diffusion of non-hydro renewable energy (NHRE) technologies for electricity generation in 108 developing countries between 1980 and 2010. Unlike previous authors, they computed the two-part model (Duan et al., 1984) and Heckman (1979) two-step selection models. The results reveal that that the diffusion of NHRE accelerates with the implementation of economic and regulatory instruments, higher per capita income and higher levels of education, as well as stable and democratic regimes. In addition, increasing openness and aid, institutional and policy support programmes, growth in electricity consumption and high fossil fuel production appear to delay the diffusion of NHRE.

Finally, energy consumption and CO2 emissions are two of the most widely debated factors in the literature. Policies and strategies to support RE development and promote energy efficiency are expected to result in lower consumption and therefore lower CO2 emissions. For example, Upton and Snyder (2017) show that states with RPS have experienced increases in electricity prices and decreases in electricity demand compared with non-RPS states with similar economic, political and renewable natural resource characteristics. However, the impact of CO2 on RE deployment still remains unclear in the literature. Environmental considerations do not seem to explain energy consumption in France (Damette et al., 2018). Indeed, when focusing on household energy consumption and transition to cleaner energy sources, Damette et al. (2018) show that individuals who claim to be sensitive to environmental issues tend to make their energy consumption decisions only on the basis of energy equipment cost and level of income. In fact, Marques et al. (2010), Marques and Fuinhas (2011) and Damette and Marques...
Pillai, 2015; Sommerfeld et al., 2017; Yu et al., 2002; Junginger et al., 2005; Li et al., 2019; Nemet, & Söderholm, 2010; Goodrich et al., 2013; Graziano & Gillingham, 2014; Hitaj & Löschel, 2019; Ibenholt, these authors noted that:

particular (Balta-Ozkan et al., 2015; Cai et al., 2013; Ek 2019) report a negative correlation between CO2 and RE deployment, whereas Aguirre and Ikikunle (2014) and Omri and Nguyen (2014) find a positive relationship. Using a novel panel cointegration approach with recent econometric tests, including different forms of cross-sectional dependence and breaks, Damette and Marques (2019) surprisingly find evidence that contradicts claims that the presence of environmental concerns boosts RE production. In addition, energy consumption (demand effect) and energy dependency have a positive impact on the deployment of renewables. Other factors, such as oil prices, seem to be potential RE drivers because in certain cases RE can replace fossil fuels including oil, but according to them, international energy prices are not a significant factor in the promotion of the RE. They explain the presence of a substitution effect as a consequence of political decisions, policy guidance and international commitments, rather than as a consequence of the competitive mechanisms of the energy market. In any case, low-carbon technologies are more expensive than fossil fuel technologies, which means that government support is essential to promoting the transition. Technological improvements would also make RE more competitive, hence the interest of the work carried out by Popp et al. (2011). Indeed, using the increase in global technology stock as a proxy for technological innovations, they show that technological advances lead to bigger investments and then renewables production, but in a small manner. Investments in other carbon-free energy sources, such as hydropower and nuclear power, seem to replace RE investments.

Natural resource endowment (Carley, 2009; Menz & Vachon, 2006) and political ideology (Cadoret & Padovan, 2016) are also identified as potential drivers in the literature. In fact, Menz and Vachon (2006) show that the natural wind resource endowment is an important factor for wind power development, while in Carley (2009), the amount of windy land area is negatively associated with the RE share. We can also mention cultural factors that could facilitate the enactment of RE policies or influence the political system (Sims Gallagher, 2013) or minimum distances between renewable power plants and human settlements (Drechsler et al., 2017). Indeed, these authors noted that:

a larger minimum settlement distance would reduce the magnitude of external costs but also lead to a shift of renewable power plants to less productive sites implying a spatially more even allocation of power plants and higher average production costs.

It is also important to focus more on the local factors that explain RE deployment. In this vein, some studies have paid more attention to the microeconomic dimension, and to the domestic adoption of PV and wind energy in particular (Balta-Ozkan et al., 2015; Cai et al., 2013; Ek & Söderholm, 2010; Goodrich et al., 2013; Graziano & Gillingham, 2014; Hitaj & Löschel, 2019; Ibenholt, 2002; Junger et al., 2005; Li et al., 2019; Nemet, 2006; Pillai, 2015; Sommerfeld et al., 2017; Yu et al., 2012). Graziano and Gillingham (2014) use detailed data on PV installations in Connecticut and identify the spatial patterns of diffusion, which indicate considerable clustering of adoptions. They show also a strong correlation between adoption and the number of systems previously installed nearby, in addition to the built environment and policy variables.

THE SPATIAL DISTRIBUTION OF RENEWABLE ENERGY IN METROPOLITAN FRANCE

RE deployment as an endogenous variable

RE deployment is the result of a multi-actor system with potential contradictory incentives (Michalena & Angeon, 2009). Authorities are the first category and implement national and European legislation whereas local authorities are supposed to accompany and organize the decision-making process and apply the final collective decision in interaction with others actors (consumers, firms, etc.). In this way, we have collected data for two French local governments and so administrative subdivisions at a regional level (régions) and at a departmental level (départements). Indeed, as previously explained, regions and departments are the local governments in charge of the energy transition in France. They encourage, promote and finance innovations in RE. In our empirical model we have considered RE deployment as an endogenous variable at both regional and departmental levels. For space and empirical reasons, we will focus on the analysis of departments considering the higher sample size, accuracy and greater data availability. In addition, there is some heterogeneity within a given region that we try to investigate. Data for all French regions have been collected (excluding Corsica) between 2008 and 2016. Thus, we are able to capture spatial and temporal heterogeneity and the recent surge in RE deployment.

Some general stylized facts

If we first look at a regional level, it comes that the growth in RE production was stable but heterogeneous (Figure 5). RE deployment is highest in regions such as Nouvelle-Aquitaine, Haut de France and Grand Est, but less important in other ones. Figures 3 and 4 describe the regional contribution to the national RE production. For solar energy, the average production amounted to between 40 and 806 GWh (attained by Ile—de—France and Occitanie, respectively) with substantial growth which had stabilized since 2013 (see Figure A2 in the supplemental data online). Solar production is mostly concentrated in the south (Occitanie, Nouvelle Aquitaine, Provence Alpes Côte d’Azur (PACA), Auvergne) (Figure 3 and see Figure A1(a) in the supplemental data online). This performance could be explained by the regions’ geographical position (sunshine) because they are located in the southernmost part of France and have a favourable situation for solar development.7 At the international level, France ranked eighth in 2015 with 2.9% of the total solar energy supply,
behind Germany (15.7%), Italy (9.3%), the UK (3.4%) and Spain (3.1%).

For wind energy, global production is estimated at around 162 TWh. France’s share is estimated at only 2.5% (far from United States and China who individually represent 23% of the production), which is mainly driven by deployment in the Grand Est region, which records the highest performance, followed by Hauts-de-France. Wind energy generation rose strongly over the period 2008–16, but it increased more slowly than solar energy (see Figure A3 in the supplemental data online). Wind energy is produced throughout the entire country, but is more concentrated in the north-east (Figure 3 and see Figure A1(b) in the supplemental data online). The lowest production is found in the Ile-de-France region, which seems more oriented toward bioenergy. The active deployment of bioenergy in this region could be explained by the fact that it is not very sunny or windy, the existence of a large agricultural sector, and the development of household waste incineration plants (renewable fraction). Indeed, bioenergy is distributed throughout all French regions with particular concentrations in Nouvelle-Aquitaine, Ile-de-France and Auvergne-Rhône-Alpes (Figure 4 and see Figure A1(c) in the supplemental data online).

Spatial distribution for departments
We complete the previous general analysis using data published by the Ministry of Sustainable Development about installed capacity in French departments; data are available per RE sector (solar, wind, bioenergy) from 2010 to 2017. The analysis of the departments data confirms the trend noted in previous regional data and provides a clearer picture of the spatial distribution of RE in France.

Table 1 shows the descriptive statistics of RE installed capacities in MW. The average installed capacity has increased over the period 2010–17 for all the considered sectors: from 11,045 to 74,36 MW for solar and from 7738 MW to 47,333 MW for wind. For wind power the
installed capacity increased by 193% during this period with a 141.9 MW average capacity.

The regional solar energy production (in 2016) was concentrated in the areas located in the south of France. However, there are disparities between departments within the same region (Figure 3). In the Occitanie region, for example, the departments of Gard, Hérault, Haute Garonne, Aude and Tarn account for nearly 60% of installed capacity. The performances achieved in Nouvelle-Aquitaine are mainly driven by the Gironde and Landes, which represent almost 60% of installed capacity. In the PACA region, the departments of Var and Alpes-de-Haute-Provence both account for 28% of the deployed capacity, followed by Bouches du Rhône with 26%, 10% for Vaucluse, and 4% for the departments of Hautes-Alpes and Alpes-Maritimes. The deployment is less dispersed in Auvergne-Rhône-Alpes compared with the PACA, Occitanie and Nouvelle-Aquitaine regions. The average deployed capacity is about 56 MW, and half of the departments in the Auvergne-Rhône-Alpes region have more than 57 MW of installed capacity.

For wind energy deployment, in the Grand Est region, the deployment is higher in the departments of Marne, Aube, Meuse and Ardennes, which represent more than 75% of the deployed capacity. In the same way, in Hauts-de-France, the Somme and Pas-de-Calais departments account for 65% of deployed capacity, which is concentrated in the departments of Loire-Atlantique (320 MW), Morbihan (328 MW) and Côtes d’Armor (301 MW).

Bioenergy is deployed throughout the central French regions, but it is higher in Nouvelle-Aquitaine and Ille-de-France (Figure 4). The deployed capacities in the Gironde, Landes and Lot-et-Garonne departments represent around 62% of installed capacity in the Nouvelle Aquitaine region. In Ille-de-France, more than 90% of the capacity has been deployed in the Val-d’Oise (37%), Essonne (22%) and Seine-et-Marne (32%) departments. However, comparison at a purely departmental level shows that Bouches du Rhône leads the way with around 22 MW.

In conclusion, the RE deployment is very heterogeneous within departments located in the same region. This disparity can be attributed to the geophysical, political and socio-economic factors. We conduct an investigation of potential determinants in the next section.

**DETERMINANTS OF RENEWABLE ENERGY DEPLOYMENT**

The previous section presented an overview of the literature and identified the key factors explaining RE deployment mostly at a country level. In this paper, we focus on a local level. However, due to constraints related to data availability at the French department level, we only focus on some main factors: socio-economic drivers (GDP, indebtedness, density), political affiliations (left/right party), geographical variables (area, location) and natural wind and solar resources endowments.

**Socio-economic variables**
French departments with a higher level of socio-economic development (GDP, Debt) are more likely to promote and invest in RE deployment.

**Income (GDP per capita)**
As the cost of RE deployment is high, high-income departments have more financial leeway to support it than low-income departments. Similarly, a high level of income is associated with low environmental degradation (high environmental protection) and the promotion of a low-carbon economy (Aguirre & Ibikunle, 2014; Damette & Marques, 2019; Omri & Nguyen, 2014; Polzin et al., 2015). In this study we use regional GDP per capita. On average, it is equal to €31,019 in 2017 and for the richest region it is about €58,300, while it is €24,700 for the less rich region.
Table 2. Independent variables, 2017.

| Variables     | Description                                      | Mean   | SD    | Minimum | Maximum  |
|---------------|--------------------------------------------------|--------|-------|---------|----------|
| GDP/capita    | Gross domestic product (GDP) per capita in euros | 31,019.4 | 8293.7 | 24,700.0 | 58,300.0 |
| Debt/capita   | Debt per capita (€)                               | 547.8 | 257.7 | 0.0 | 1376.8 |
| Density       | Inhabitants/km²                                   | 574.4 | 2485.2 | 14.8 | 21,066.8 |
| Sunshine      | Hours of sunshine                                | 1999.0 | 353.3 | 1287.0 | 3032.0 |
| Wind speed    | Maximum wind speed (km/h)                        | 33.7 | 5.4 | 25.0 | 53.0 |
| AREA          | km²                                              | 5694.5 | 1933.7 | 105.4 | 10,000.1 |
| Politic       | Describing the political colour of regions       |        |       |         |          |
| South-East    | Dummy variable                                   |        |       |         |          |
| South-West    | Dummy variable                                   |        |       |         |          |
| North-East    | Dummy variable                                   |        |       |         |          |
| North-West    | Dummy variable                                   |        |       |         |          |

Scale
1 = Left 0 = right

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**Figure 5.** Departmental renewable energy (RE) deployment, 2016.
Source: Authors.
Indebtedness (debt per capita)
The local governments organize and promote investments in small RE projects via Société Publique Locale (SPL) (local public firms) and help more important RE projects by giving subsidies or by buying equities of private firms. If fiscal revenues are not enough important, indebtedness is likely to be a proxy of a positive RE deployment. Indeed, when local authorities do not have sufficient resources to cover all their expenditures and investments, they may therefore resort to debt financing in order to achieve their RE goals. For this purpose, they may issue bonds, cash certificates or collect private savings. Kim and Park (2016) have shown that the speed of the RE deployment is dependent on debt and equity financing and of financial markets development. Here we use the debt per capita (Table 2), but we also test the squared debt. Indeed, a too high level of indebtedness – when the debt surpasses a sustainable threshold – could be counter-productive and slow down the RE investments projects. This situation is plausible since the aftermaths of the 2008 subprime crisis have amplified the debt of French local governments and thus the systemic risk of bankruptcy for French departments (Frouté, 2021).

Population density
RE deployment is likely to be negatively associated with population density for two reasons. First, RE deployment (large scale) – by creating solar and wind farms, for example – requires large amounts of space, which are often available in isolated (rural) and less densely populated areas. The second reason relates to the resistance of populations deterred by the noise of wind turbines or their aesthetic impact on the landscape. However, even though it has not been conclusively proven that proximity to a wind turbine or wind farm negatively affects stress responses, quality of life, quality of sleep or other problems of health (van Kamp & van den Berg, 2018), policymakers should take a precautionary approach to address more deeply the factors that contribute to the frustration of host communities (Fast et al., 2016). The higher uptake of solar energy in less densely populated areas is due to the higher proportion of single- and double-family homes (Balta-Ozkan et al., 2015). Based on these observations and on regulatory constraints (distance between houses and turbines, the impossibility to install turbines in zones with military radars, for instance), some geographers now believe that the maximum number of wind turbines that could be installed has almost been reached in the Lorraine region. Our data show that the density of French departments is very dispersed. The least dense department has 14.8 inhabitants/km² for an average of 574.4 inhabitants/km².

Political ideology
The political ideology of the department can influence RE deployment if the departmental council (Conseil Général) is controlled or influenced by a pro-environmental. Failing to have data on the potential pressure of lobbies environmentalists and the green energy industry, we test if departments controlled by a left-wing party have a different impact on RE deployment compared with those with a right–left party.

Indeed, political ideology is likely to play an important role in determining RE development (Carley, 2009; Menz & Vachon, 2006; Upton & Snyder, 2017), as is the country’s membership of the EU (Marques et al., 2010). The government’s ideology is also a political factor that potentially affects the environmental quality and the stringency of energy policies (Cadoret & Padovano, 2016). At the household level, Mildenberger et al. (2019), investigating the political identities of solar energy adoption in the United States, show that solar household residents are slightly more likely to be Democrats. In this study, we expect that left-wing parties (dummy variable) are more likely to encourage RE deployment (Cadoret & Padovano, 2016) by supporting greater investment. Note that since 2017, 24% of the departments of metropolitan France are managed by a left party.

Geographical area and features
A larger geographical area is assumed to be positively correlated with RE production (Marques et al., 2010). Thus, we add the surface of departments as a control variable. We also control for spatial dummies by taking into account the special geographical characteristics of the French territory.

Geographical area
Larger departments have greater potential for the deployment of REs. Indeed, space constraints are one obstacle to RE deployment. For example, wind power is seen by many observers as an important part of the transition to a sustainable energy system (Khan, 2003), but its deployment in France is subject to landscape regulations, which impose a minimum distance of 500 m between dwellings and wind turbines. This implies that departments with larger surface areas have greater potential to promote RE, and vice versa.

Natural solar and wind resource endowments
A descriptive statistics analysis shows that RE production is more concentrated in certain departments: solar energy deployment in southern departments and wind energy deployment in the north. Indeed, the geographical location of the departments could enable them to benefit from particular physical conditions that are favourable to RE production (wind speed and frequency for wind energy and solar radiation and sunshine for solar). The amount of sunshine (hours of sunshine) and wind speed (km/h) are used since they are likely to have a direct and positive impact on the deployment of solar and wind energy, respectively.

RENEWABLE ENERGY SUPPLY MODELLING
In this section we present the econometric model considered to assess the determinants of RE deployment in France considering data about departments. We first consider a non-spatial panel and then test the possibility of...
extending this baseline model to include spatial interaction effects.

We assume that RE deployment depends on several factors according to the following relationship:

\[ Y_{it}^E = f(X_{it}, V_{it}, Z_{it}) \]  

where \( X_{it}, V_{it} \) and \( Z_{it} \) are a set of explanatory variable vectors describing socio-economic characteristics, geophysical variables, political and environmental factors, respectively. The RE deployment in department \( i = 1, \ldots, N \) in time \( t = 1, \ldots, T \) is noted \( Y_{it}^E \) with \( F = \) (solar, wind, bioenergy).

From equation (1), we can write the fixed-effect specification as follows:

\[ Y_{it}^E = \beta^i X_{it} + \phi^i V_{it} + \delta^i Z_{it} + \eta_{it} \]  

with:

\[ \eta_{it} = \alpha_t + e_{it} \]  

where the \( \alpha_t \) parameters are the fixed effects of the departments \( t \), which are assumed to be IID \((0; \sigma^2_{\alpha})\); it captures unobserved heterogeneity across individuals that is fixed over time. \( \beta^i, \phi^i \) and \( \delta^i \) are the vectors of parameters associated with the explanatory variable vectors \( X_{it}, V_{it} \) and \( Z_{it} \).

However, equation (2) ignores possible spatial dependence in RE deployment. Indeed, the interactions between departments could lead to spatial autocorrelation. Ignoring this fact could therefore lead to violation of the error independence assumption (LeSage & Pace, 2009). According to Anselin (1988) and Anselin et al. (2013), spatial dependence leads to bias in OLS estimates if it concerns the dependent variable. Several tests can therefore be used to detect spatial dependence between departments. Classic and robust Lagrange multiplier (LM) tests, proposed by Anselin (1988) and Anselin et al. (1996), and cross-section dependence (CD) tests can be performed. The LM test has the advantage of determining the appropriate specification by taking account of spatial dependence. Indeed, it can be a spatial error term (SEM1) model, which includes a spatial autoregressive (SAR) process in the error term, or a spatial lag model, which incorporates an SAR-dependent variable:

SAR:

\[ Y_{it}^E = a \sum_{j=0}^{N} \omega_{ij} Y_{jt}^E + \beta^i X_{it} + \phi^i V_{it} + \delta^i Z_{it} + \epsilon_{it} \]  

\[ \epsilon_{it} = e_t + n_{it} \]  

SEM: \( Y_{it}^E = \beta^i X_{it} + \phi^i V_{it} + \delta^i Z_{it} + u_{it} \)  

\[ u_{it} = \mu_t + \xi_{it} \]  

\[ \xi_{it} = \lambda \sum_{j=0}^{N} \omega_{ij} \xi_{jt} + v_t \]  

\[ v_t \rightarrow N(0, \sigma^2_v) \]

where \( a \) is the SAR parameter for the spatially lagged dependent variable; and \( \lambda \) is the SAR parameter for the spatially lagged error term. These parameters describe the strength of spatial dependence. \( \omega_{ij} \) is the spatial weight matrix, with \( i \) and \( j \) representing the spatial units. There are several definitions of ‘neigh-

bord’ in the literature, which include contiguity, \( k \)-nearest neighbours and inverse distance. In the case of the contiguity matrix \( \omega_{ij} = 1 \), if \( i \) and \( j \) are spatial neighbours, that is, sharing a common border, and 0 otherwise. If the contiguity is \( k \) order, it means that there are \( k \) borders between \( i \) and \( j \), with \( k \) being the minimum number of borders. In the distance-based case:

\[ \omega_{ij} = \frac{1}{d_{ij}} \]

where \( d_{ij} \) is the distance between regions \( i \) and \( j \). To determine the appropriate weight matrix, researchers generally make an arbitrary choice of specifications that they intuitively recognize as providing the best solution (Marton, 2015), or use the existing forms of association in the literature and choose the one that seems the best. In this study, estimates will be made using the contiguity matrix. In addition, the inverse distance weight matrix, the three-, four- and five-nearest neighbours are used to check the robustness of results. Generally, spatial weight matrices are row standardized so that they sum to 1.

In equations (4) and (6), the unobserved individual effect is captured by \( \epsilon_t \) and \( \mu_t \) for the SAR and SEM models, respectively. We assume that these parameters represent the fixed effects.

**EMPIRICAL STRATEGY AND RESULTS**

**Choice of model and tests**

We begin by identifying the appropriate specification to describe the data. Thus, we considered fixed effect models without spatial autocorrelation and then used different test statistics to investigate the presence of potential spatial dependence: the LM test. This is a test for specifying spatial autocorrelation and the absence of each of the spatial terms without estimating the unconstrained model. In the same vein, the CD test allows one to test for the presence of cross-sectional dependence in panels with many cross-sectional units and few time-series observations (for more details, see De Hoyos & Sarafidis, 2006).

The Pesaran (CD) and LM tests reveal the existence of spatial autocorrelation (see Table A2 in the supplemental data online), meaning that there is a functional relationship between what happens at one point in space and what happens elsewhere (Le Gallo, 2004). Ignoring spatial interactions could lead to biased and inconsistent estimates.

As well as detecting the presence of spatial autocorrelation, the LM tests (LMlag, LMlerr) and the robust versions (RLMlag, RLMlerr) (Anselin, 1988; Anselin et al., 1996) allow for discrimination between the SAR and SEM models. The SEM specification is preferred for all...
sctors (solar, wind and bioenergy): the hypotheses of no spatial lag and no spatial autocorrelated error term are strongly rejected for solar energy and bioenergy. Examining the RLMlag and RLMlerr tests, both hypotheses are rejected for all specifications, apart from RLMlag for solar. In addition, the statistics associated with RLMlerr are the highest values, indicating an SEM specification. In the following section we will estimate both SEM and SAR models and use Akaike information criterion (AIC) and loglikelihood criteria to choose the optimal one. However, the spatial models (SEM or SAR) do not take into account the time persistence effect that is only detected by the Wooldridge test. The results from the Wooldridge test confirm the presence of serial correlation. Besides the Wooldridge test, the conditional LM tests for the panel data model including a joint test for serial correlation, spatial autocorrelation and random effects proposed by Baltagi et al. (2007) are also performed. The one-dimensional conditional test for zero random region effects, allowing for the presence of both serial and spatial error correlation, is performed and the null hypothesis \( H_0: \sigma^2 = 0 \) (allowing \( \rho \neq 0 \) and \( \lambda \neq 0 \)) is not rejected. Ignoring these correlations, whether spatial at a point in time or serial correlation for a spatial unit over time, may lead to a misleading inference (Baltagi et al., 2007). Therefore, a spatial model alone is not sufficient to describe the characteristics of the data, and it is necessary to find a more suitable specification that takes both spatial and serial correlation into account. Marques and Fuinhas (2012) estimated panel models with a first-order autoregressive disturbance term in order to eliminate serially correlated errors. However, in contrast to their study, we follow Millo (2014) by assuming the presence of serial correlation in the remainder of the error term from the SAR and SEM models. We called these models the SARsr and SEMsr models to remain consistent with the term used by Millo. In the SARsr and SEMsr models, it is assumed that the respective error terms of equations (4) and (6) follow an autoregressive process of order 1:

\[
\begin{align*}
    n_{it} &= \rho n_{i,t-1} + \epsilon_t \\
    v_{it} &= \rho' v_{i,t-1} + r_t
\end{align*}
\]

where \( n_{it} \) and \( v_{it} \) are independent and identically distributed. The SARsr model assumes spatial spillover effects in the dependent variable from neighbouring regions (SAR) and time persistence or serial correlation (SR); the SEMsr model assumes spatial spillover effects in the error (SEM) and serial correlation (SR).

**Results**

We begin by estimating a pooled OLS model (Table 3) and then the SAR and SEM models (Table 4). We identified three specifications: a pooled model without fixed effect, a model with individual fixed effects and a model in which we introduced the dummy variable related to geographical location. The potential links between our explanatory variables can lead to the existence of multicollinearity among these variables that is not confirmed by the reported correlation matrix (see Table A9 in the supplemental data online) and the variance inflation factor (VIF) tests performed.

The results derived by estimating the pooled OLS model reflect the existence of some spatial and serial dependences in the data. Indeed, the presence of spatial correlation is confirmed by the LM test, whereas the Wooldridge test confirms the presence of serial correlation (see Table A2 in the supplemental data online). Consequently, a spatial econometric model taking into account serial correlation is more relevant to describe the characteristics of our data.

The results obtained by the SAR and SEM models (Table 4) are very similar. The estimated coefficient associated with the spatial lagged (SAR) model is only positive and statistically significant for solar energy and bioenergy cases. Similarly, the spatial error term coefficient of the SEM model, which indicates the response of RE deployment of a given department to an exogenous shock in a neighbouring department, is also positive and significant for the same sources. These coefficients are negative and not significant for wind energy. However, if we take serial correlation into account, the spatial lag (for the SAR model) and the spatial error term (for the SEM model) turn out to be also positive and significant.

These discrepancies could be explained by a potential bias in the SAR and SEM models due to the potential presence of serial correlation and confirm the relevance of estimating SARsr and SEMsr in this paper. A comparison of the SARsr and SEMsr models according to the AIC and log-likelihood criteria shows the SARsr model is the best. Interpreting the parameters of the models containing spatial lag for the explanatory or dependent variables is a complex undertaking that requires a cautious analysis (LeSage & Pace, 2009). Therefore, like LeSage (2008), we calculated the marginal effects in order to distinguish between the direct, indirect and total impacts. A change in a single observation associated with any given explanatory variable will affect the department itself (direct impact) and potentially affect all others indirectly (indirect impact) (LeSage & Pace, 2009).

**Spatial spillovers effect**

The spatial autoregressive parameters associated with the spatial lag of RE deployment are positive and significant. It reveals the existence of positive geographical spillovers and confirms the role of proximity in RE deployment, whatever the econometric specifications considered. Our results indicate an important spatial neighbour effect, especially for solar energy (highest coefficients). The new technology’s diffusion is a dynamic process, which often exhibits a characteristic spatial pattern over time (Graziano & Gillingham, 2014). Geographical spillovers in RE deployment can be attributed to the natural resource endowment (wind, sunshine and space) and the influence of energy policies. For example, solar deployment can be a consequence of peer effects (Rai et al., 2016) or imitation ones resulting from a competition effect between the local policymakers.
The spatial interaction can also result in the network charge between departments. Indeed, the forecast cost of network is supported by the producers. However, there are large disparities in the network charge between regions. In Alsace, for example, this share is zero (€0), in Nord-Pas-de-Calais it is fixed at €9.19/kW, while in Picardie, a neighbouring region, it is €58.67/kW. In Midi-Pyrénées, it even reaches €69.85/kW. This differentiated network charge between department enhances locational arbitrage opportunities.

The role of socio-economic variables
Socio-economic variables seem to play a significant role on RE deployment (Table 5). GDP has a direct and significant positive effect on solar and bioenergy deployments. An increase in the GDP of a given department will positively affect solar energy and bioenergy deployment. The magnitude of the indirect effect is estimated at 17% (specification 2) and 22% (specification 3) of the total effect for solar energy. For bioenergy, it is evaluated at 9% and 12%.

The costs associated with promoting a low-carbon economy are high, which means that high-income departments (high GDP per capita) have more leeway than low-income ones. In contrast, for wind energy, the income is only significant for the specification (3). This result could be explained by the existence of regulatory constraints in order to protect natural areas and the life quality of inhabitants. In other words, high-income departments that do not have enough space to conform to the regional wind patterns will not be able to implement wind energy projects whatever the income level. For example, wind energy is more highly developed in the north-east areas, particularly in the Grand Est, which was ranked only seventh in the classification of regions according to GDP in 2016. The distance of 500 m between dwellings and wind turbines is one of the constraints imposed on new wind farm installations. Hence, the importance of economics drivers can be reduced by the importance regulatory and other determinants (population density, laws to protect biodiversity etc.).

Table 3. Ordinary least squares (OLS) (pooling) estimation results.

| Dependent variable | Solar | Wind | Bioenergy |
|--------------------|-------|------|-----------|
|                    | (1)   | (2)  | (1)       | (2)     | (1)     | (2)    |
| GDP                | 1.7136* | 1.7915* | -3.4888** | -3.6706** | 0.1956*** | 0.1907*** |
| (1.0174)           | (0.9763) | (1.5485) | (1.5790) | (0.0702) | (0.0701) |
| Politic            | 11.8951 | 3.7970 | -46.4204** | -29.1513 | -0.4702 | -0.2799 |
| (8.0285)           | (6.5064) | (20.1900) | (18.5501) | (0.4918) | (0.4749) |
| Indebtedness       | 0.6600* | 0.8037** | 0.0316 | -0.9640 | 0.0074 | -0.0039 |
| (0.3604)           | (0.3525) | (1.1415) | (1.0084) | (0.0426) | (0.0431) |
| Indebtedness²      | -0.0064** | -0.0081*** | -0.0054 | 0.0037 | -0.0002 | -0.0001 |
| (0.0032)           | (0.0030) | (0.0073) | (0.0066) | (0.0003) | (0.0003) |
| Density            | 0.0140 | 0.0148 | 0.0521 | 0.0099 | -0.0041** | -0.0045** |
| (0.0132)           | (0.0128) | (0.0345) | (0.0251) | (0.0020) | (0.0020) |
| AREA               | 0.0151** | 0.0141** | 0.0149** | 0.0169** | 0.0004* | 0.0005* |
| (0.0064)           | (0.0059) | (0.0073) | (0.0077) | (0.0002) | (0.0002) |
| Sunshine           | 7.1750*** | 5.9664*** | -143.9044*** | -1.4165 | -1.1523 |
| (1.2773)           | (1.3684) | (35.7178) | (101.1781) | (101.3600) | (2.9919) |
| South-East         | 6.2706 | -143.9044*** | -1.4165 |
| (8.8926)           | (35.7178) | (1.1523) |
| South-West         | 35.0996** | -110.6018** | -1.2810 |
| (14.1589)          | (43.4079) | (0.8337) |
| North-West         | -3.0156 | -57.4274 | -0.8252 |
| (8.6417)           | (46.2067) | (0.8372) |
| Windspeed          | 0.0302 | 2.3904** |
| (1.4724)           | (1.0940) |
| Constant           | -246.0579*** | -225.9795*** | 149.3815 | 149.6619 | -4.0007 | -3.3618 |
| (79.2175)          | (74.3808) | (101.1781) | (101.3600) | (2.9919) | (2.9122) |
| F-statistic        | 35.83 | 30.08 | 13.56 | 22.39 | 13.70 | 10.85 |
| Probability        | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 |
| R²                 | 0.25 | 0.29 | 0.11 | 0.23 | 0.10 | 0.12 |

Note: *p < 0.1; **p < 0.05; ***p < 0.01; standard errors are shown in parentheses.
Table 4. Spatial autoregressive (SAR) model estimate results.

|                | Solar       | Wind       | Bioenergy  |
|----------------|-------------|------------|------------|
|                | (1)         | (2)        | (3)        | (1)         | (2)         | (3)         |
| \( a \)        | 0.1816***   | 0.1894***  | 0.1817***  | -0.0499     | 0.1790***   | -0.0730     | 0.2591***   | 0.1124***   | 0.2649***   |
|                | (0.0469)    | (0.0502)   | (0.0463)   | (0.0507)    | (0.0470)    | (0.0486)    | (0.0468)    | (0.0512)    | (0.0465)    |
| GDP            | 1.6773***   | 13.816***  | 1.7532***  | -3.6096***  | 6.2010***   | -3.8508***  | 0.2023***   | 0.9107***   | 0.1968***   |
|                | (0.3781)    | (1.4793)   | (0.3705)   | (0.9343)    | (2.1965)    | (0.8725)    | (0.0258)    | (0.0876)    | (0.0256)    |
| Politic        | 14.3349***  | 12.770***  | 6.2915     | -46.9671*** | -27.651***  | -29.8141*** | -0.2349     | -0.3683     | -0.0238     |
|                | (4.2816)    | (4.6932)   | (4.3719)   | (10.5412)   | (6.9569)    | (10.3022)   | (0.2913)    | (0.2778)    | (0.3032)    |
| Indebtedness   | 0.6193**    | 2.7952***  | 0.7560***  | 0.0036      | 0.3277      | -1.0120*    | 0.0001      | 0.1505***   | -0.0120     |
|                | (0.2647)    | (0.6415)   | (0.2610)   | (0.6516)    | (0.9460)    | (0.6153)    | (0.0180)    | (0.0378)    | (0.181)     |
| Indebtedness\(^2\) | -0.0060*** | -0.0159*** | -0.0077*** | -0.0049     | 0.0045      | 0.0045      | -0.0002     | -0.0011***  | -0.0001     |
|                | (0.0020)    | (0.0054)   | (0.0020)   | (0.0050)    | (0.0080)    | (0.0048)    | (0.0001)    | (0.0004)    | (0.0001)    |
| Density        | 0.0074      | -2.1467*** | 0.0080     | 0.0512*     | -2.4983***  | 0.0083      | -0.0045***  | -0.1474***  | -0.0049***  |
|                | (0.0117)    | (0.6947)   | (0.0115)   | (0.0289)    | (1.0317)    | (0.0272)    | (0.0008)    | (0.0008)    | (0.0008)    |
| AREA           | 0.0146***   | 0.0137***  | 0.0147***  | 0.0167***   | 0.0004***   | 0.0005***   | 0.0001      | 0.0001      |
|                | (0.0015)    | (0.0015)   | (0.0037)   | (0.0035)    | (0.0001)    | (0.0001)    | (0.0001)    |
| Sunshine       | 7.0784***   | 0.2906     | 5.9374***  | -0.1035     | -0.1205     | 2.2061**    | (0.9857)    | (0.6014)    | (0.9426)    |
|                | (0.6452)    | (0.7838)   | (0.7778)   | (0.9857)    | (0.6014)    | (0.9426)    |
| Windspeed      | -0.1035     | -0.1205    | 2.2061**   | (0.9857)    | (0.6014)    | (0.9426)    |
| South-East     | 5.1050      | 144.5446***| -1.4007*** |
|                | (7.0725)    | (14.2239)  |
| South-West     | 34.1402***  | -111.4970***| -1.3814*** |
|                | (6.6262)    | (14.4429)  |
| North-West     | -3.9662     | -57.9460***| -0.8879** |
|                | (6.1169)    | (14.3678)  |
| Constant       | -249.1990***| -229.8180***| 163.8020***| 170.8714*** | -4.8554***  | -4.0145***  |
|                | (23.3567)   | (23.9255)  | (55.7998)  | (52.1140)   | (1.2882)    | (1.2960)    |
| Individual FE  | No          | Yes        | No         | No          | Yes         | No          | No         |
| Geo-location FE| No          | No         | Yes        | No          | Yes         | Yes         | Yes        |

(Continued)
# Spatial error model (SEM)

|       | Solar          | Wind          | Bioenergy     |
|-------|----------------|---------------|---------------|
|       | (1)            | (2)           | (3)           | (1)            | (2)           | (3)           |
| $\lambda$ | 0.2374*** | 0.0674 | 0.2302*** | $-0.0916$ | $0.1166^{**}$ | $-0.0564$ | $0.3211^{***}$ | $0.0397$ | $0.3167^{***}$ |
|        | $(0.0509)$    | $(0.0628)$    | $(0.0512)$    | $(0.0573)$  | $(0.0586)$  | $(0.0546)$  | $(0.0476)$  | $(0.0567)$  | $(0.0476)$  |
| GDP   | 1.6451*** | 16.057*** | 1.8043*** | $-3.7612^{***}$ | $7.3927^{***}$ | $-3.7074^{***}$ | $0.2202^{***}$ | $0.9965^{***}$ | $0.2066^{***}$ |
|        | $(0.3786)$    | $(1.5511)$    | $(0.3728)$    | $(0.9274)$  | $(2.3589)$  | $(0.8698)$  | $(0.0257)$  | $(0.0898)$  | $(0.0258)$  |
| Politic | 17.9538*** | 11.579*** | 10.0242*** | $-48.6561^{***}$ | $-28.828^{***}$ | $-30.7372^{***}$ | $0.0780$ | $-0.4129$ | $0.2776$ |
|        | $(4.3096)$    | $(4.7642)$    | $(4.4019)$    | $(10.4376)$ | $(7.0604)$  | $(10.2595)$ | $(0.2908)$  | $(0.2796)$  | $(0.3038)$  |
| Indebtedness | 0.4717* | 2.8288*** | 0.6455*** | $-0.0001$ | $0.3929$ | $-0.9721$ | $-0.0094$ | $0.1530^{***}$ | $-0.0209$ |
|        | $(0.2649)$    | $(0.6474)$    | $(0.2621)$    | $(0.6464)$  | $(0.9496)$  | $(0.6135)$  | $(0.0179)$  | $(0.0379)$  | $(0.0181)$  |
| Indebtedness$^2$ | $-0.0050^{**}$ | $-0.0159^{***}$ | $-0.0069^{***}$ | $-0.0045$ | $0.0040$ | $0.0041$ | $-0.0001$ | $-0.0011^{***}$ | $-0.0001$ |
|        | $(0.0020)$    | $(0.0055)$    | $(0.0020)$    | $(0.0050)$  | $(0.0080)$  | $(0.0047)$  | $(0.0001)$  | $(0.0003)$  | $(0.0001)$  |
| Density | $-0.0003$ | $-2.3351^{***}$ | $-0.0002$ | $0.0463$ | $-2.6277^{***}$ | $0.0066$ | $-0.0052^{***}$ | $-0.1552^{***}$ | $-0.0055^{***}$ |
|        | $(0.0118)$    | $(0.7056)$    | $(0.0116)$    | $(0.0286)$  | $(1.0472)$  | $(0.0271)$  | $(0.0008)$  | $(0.0414)$  | $(0.0008)$  |
| AREA   | 0.0137*** | 0.0127*** | 0.0145*** | $0.0167^{***}$ | $0.0004^{***}$ | $0.0004^{***}$ | $0.0001$ | $0.0001$ |
|        | $(0.0014)$    | $(0.0014)$    | $(0.0037)$    | $(0.0035)$  | $(0.0001)$  | $(0.0001)$  | $(0.0001)$  | $(0.0001)$  |
| Sunshine | 7.2272*** | 0.3258 | 6.1647*** | $-0.2959$ | $-0.1562$ | $2.2832^{**}$ | $(0.9783)$ | $(0.6105)$ | $(0.9432)$ |
|        | $(0.6612)$    | $(0.8109)$    | $(0.7957)$    | $(0.9783)$  | $(0.6105)$  | $(0.9432)$  | $(0.0001)$  | $(0.0001)$  | $(0.0001)$  |
| Windspeed | | | | | | | | | |
| South-East | 3.7693 | | | $-142.7682^{***}$ | | $-1.2632^{***}$ |
| | $(7.0955)$ | | | $(14.2289)$ | | $(0.4092)$ |
| South-West | 33.8573*** | | | $-109.7294^{***}$ | | $-1.3281^{***}$ |
| | $(6.7344)$ | | | $(14.3809)$ | | $(0.4280)$ |
| North-West | $-2.7977$ | | | $-56.8051^{***}$ | | $-0.7574^*$ |
| | $(6.0588)$ | | | $(14.3954)$ | | $(0.4132)$ |
| Constant | $-233.7810^{***}$ | | | $-219.1822^{***}$ | | $-4.2526^{***}$ | | $-3.1936^{**}$ |
| | $(23.4110)$ | | | $(23.8626)$ | | $(1.2528)$ | | $(1.2801)$ |
| Individual FE | No | Yes | No | No | Yes | No | No | Yes | No |
| Geo-location FE | No | No | Yes | No | No | Yes | No | No | Yes |

**Note:** *p < 0.1; **p < 0.05; ***p < 0.01; standard errors are shown in parentheses. In model (1), the fixed effect (FE) is not taken into account. Model (2) takes into account the individual FE, while in model (3) we introduced dummy variables to capture the geographical location of department.
Table 5. Renewable energy (RE) deployment estimation results: direct and indirect spatial effects.

(a)

|                | Solar                  | Wind                   | Bioenergy               |
|----------------|------------------------|------------------------|-------------------------|
|                | (1)        | (2)         | (3)        | (1)        | (2)         | (3)        | (1)        | (2)         | (3)        |
| GDP            | 4.1454*** | 10.2499*** | 4.0983*** | 1.4215     | 6.6657***  | 0.9178     | 0.2204***  | 0.7727***  | 0.2148***  |
|                | (4.594)    | (7.6186)    | (4.650)    | (0.752)    | (2.9497)   | (0.451)    | (4.158)    | (8.094)    | (4.128)    |
| Indebtedness   | 1.0831**  | 1.6401***  | 1.1650***  | −0.0962    | 0.0250     | −0.3312    | 0.0342     | 0.1381***  | 0.0249     |
|                | (2.231)    | (3.0708)    | (−2.072)   | (−0.144)   | (0.032)    | (−0.325)   | (0.979)    | (3.436)    | (0.728)    |
| Indebtedness^2 | −0.0065*  | −0.0091**  | −0.0076*   | 0.0028     | 0.0058     | 0.0048     | −0.0004    | −0.0010*** | −0.0003    |
|                | (−1.712)   | (−2.1247)   | (2.435)    | (0.411)    | (0.763)    | (0.608)    | (−1.461)   | (−2.878)   | (−1.153)   |
| Density        | −0.0146   | −0.9382    | −0.0071    | 0.0138     | −1.1833    | −0.0162    | −0.0042**  | −0.1131**  | −0.0046***  |
|                | (−0.423)   | (−1.4574)   | (−0.223)   | (0.180)    | (−1.036)   | (−0.189)   | (−2.333)   | (−2.363)   | (−2.649)   |
| Policy         | 2.8032    | 5.0657     | 2.0725     | −16.3322** | −16.7402** | −16.0850** | −0.7252**  | −0.5605*   | −0.6777**  |
|                | (0.828)    | (1.388)     | (0.578)    | (−2.568)   | (−2.5331)  | (−2.542)   | (−2.211)   | (−1.819)   | (−2.073)   |
| AREA           | 0.0203*** | 0.0182***  | 0.0259**   | 0.00045    | 0.0290***  | 0.0005**   | (Continued) |            |            |
| Sunshine       | 0.7104**  | 0.3360     | 0.6388*    | (4.647)    | (4.161)    | (2.447)    | (1.972)    | (2.882)    | (2.226)    |
|                | (2.065)    | (0.9215)    | (1.860)    |            |            |            |            |            |            |
| Wind speed     |           | 0.1393     | 0.0021     | 0.1757     | (0.387)    | (0.013)    | (0.520)    |            |            |
| South-East     |           |            |           | 30.0400*   | (1.676)    | (−3.446)   | (−1.4971)* |            |            |
| South-West     |           |            |           | 53.4674*** | (3.136)    | (−2.864)   | (−1.665)   |            |            |
| North-West     |           |            |           | 5.4939     | (0.308)    | (−1.075)   | (−1.640)   |            |            |
| Individual     | No        | Yes        | No        | No         | Yes        | No         | No         | Yes        | No         |
| Geo-location   | No        | No         | Yes       | No         | No         | Yes        | No         | No         | Yes        |
|                | (Continued) |            |            |            |            |            |            |            |            |
### (b) Indirect effect

|                | Solar                  | Wind                  | Bioenergy               |
|----------------|------------------------|-----------------------|-------------------------|
|                | (1) (2) (3)            | (1) (2) (3)           | (1) (2) (3)             |
| GDP            | 1.1897*** 2.2305*** 1.1884*** | 0.2600 1.3644** 0.1639 | 0.0289* 0.0824* −0.0289* |
|                | (2.993) (2.862) (2.957) | (0.669) (2.137) (0.421) | (1.838) (1.662) (1.807) |
| Indebtedness   | 0.3108* 3.4931*** 0.3378** | −0.0176 0.0051 −0.0591 | 0.0045 0.0147 0.0033    |
|                | (2.231) (2.154) (2.010) | (−0.151) (0.027) (−0.310) | (0.822) (1.491) (0.651) |
| Indebtedness²  | −0.0019** −0.0018* −0.0022** | 0.0005 0.0012 0.0008  | −0.0001 0.0000 0.0000    |
|                | (−1.514) (−1.696) (−1.778) | (0.398) (0.709) (0.568) | (−1.118) (1.419) (−0.930) |
| Density        | −0.0042 −0.2090 −0.0021 | 0.0025 −0.2422 −0.0029 | −0.0005 −0.0121 −0.0006    |
|                | (−0.407) (−1.303) (−0.219) | (0.173) (−0.965) (−0.169) | (−1.518) (−1.299) (−1.569) |
| Policy         | 0.8045 1.0450 0.6010 | −2.9874* −3.4267* −2.8721* | −0.0951 −0.0597 −0.0912    |
|                | (0.786) (1.192) (0.551) | (−1.841) (−1.894) (−1.819) | (−1.447) (−1.176) (−1.371) |
| AREA           | 0.00583*** 0.0053*** 0.0047* | 0.0004 0.0052** 0.0000 | 0.0000 0.0000 0.0000    |
|                | (3.063) (2.784) (1.752) | (−1.941) (−1.381) (2.002) | (1.415) (1.415) (1.415) |
| Sunsine        | 0.2039* 0.072 0.1852* | 0.0255 0.0004 0.0314 | 0.0000 0.0000 0.0000    |
|                | (1.769) (0.841) (1.622) | (0.374) (0.024) (0.484) | (1.415) (1.415) (1.415) |
| Wind speed     | 0.0255 | 0.0004 | 0.0314 | 0.0000 | 0.0000 | 0.0000 |
|                | (0.374) | (0.024) | (0.484) | (1.415) | (1.415) | (1.415) |

### Note

Z-statistics are shown in parentheses. *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$. In model (1), the fixed effect is not taken into account. Model (2) takes into account the individual fixed effect, while in model (3) we introduced dummy variables to capture the geographical location of department.
Using indebtedness as an economic support would be likely to encourage solar energy investments. The total marginal effect, consisting mainly of the direct impact, is evaluated at 5.1331 and 1.5028 for specifications 2 and 3, indicating that the use of indebtedness is favourable for the development of solar energy projects. However, a too high level of indebtedness has a direct and negative impact on the solar energy deployment. The investments in RE needed to reach the equipment rates on which France committed itself by 2030 and its climate objectives in 2050 (to divide by four the GHG emissions between 1990 and 2050) are evaluated to €225 billion for the period 2016–35. The mobilization of private capital, including bank credit, will be thus necessary to finance the development of RE in the future and the energy transition.

The political ideology variable
The political ideology effect is not clear-cut. The hypothesis that the RE deployment might increase when left-wing parties manage the departmental council Conseil Général is not confirmed. This result is observed for solar energy, but the relationship is not significant contrary to descriptive statistics (Figure 6). It is in line with the conclusion reported by Graziano and Gillingham (2014) for residential solar PV systems. In addition, wind energy and bioenergy deployments are less favourable when a left-wing party controls the departmental council. Indeed, a coefficient of approximately −16.08 (model 3) is associated with the political ideology variable, while it is estimated at −0.6777 for bioenergy.

The impact of geographical area and natural resource endowment
The coefficients measuring the effect of the surface area covered by the departments are positive and highly significant. Larger ones have more space to implement RE projects. However, the amplitude of this effect is more clear-cut for wind turbines. The use of surface area as an explanatory variable can be questioned, since a larger area does not necessarily mean better intrinsic characteristics for improving the exploitation of RE sources (Marques et al., 2010), although it increases the probability of satisfying landscape-related constraints. Moreover, it is more probable that solar and wind energy deployment will be higher in departments benefiting from higher levels of natural solar and wind resources. Our results confirm that solar energy deployment is positively correlated with sunshine levels, especially for the southern departments. Indeed, the direct marginal effect related to sunshine is positive and significant for specifications 1 and 3. However, wind energy is surprisingly more developed in less windy areas, particularly in the north-east. This result could be explained by the existence of numerous regulatory constraints that aim to conserve buffer spaces between wind turbines and inhabited areas, but also to protect natural areas. The minimum distance between wind turbines and dwellings is fixed at 500 m and the average area occupied per 3 MW wind turbine is 60–150 ha. As a result, the municipalities that meet these conditions or which are favourable to regional wind energy schemes tend to be located in the north-east and south-east regions featured by large spaces and low population density.

ROBUSTNESS CHECKS

Weight matrix
We estimated all specifications considering the inverse distance weight matrix and the three-, four- and five-near-est neighbours. The results are given in Tables A5–A8 in the supplemental data online.

The findings for solar energy confirm those obtained with the contiguity matrix. The spatial lag coefficients
Table 6. SARsr model estimation with additional explanatory variables.

|                | Solar          | Wind           | Bioenergy      |
|----------------|----------------|----------------|----------------|
|                | (1)            | (2)            | (3)            | (1)            | (2)            | (3)            |
| \(a\)         | 0.2379***      | 0.1919***      | 0.2800***      | 0.1588***      | 0.1575***      | 0.1571***      | 0.1192**       | 0.1229**       | 0.1291**       |
|                | (0.0468)       | (0.0480)       | (0.0454)       | (0.0476)       | (0.0475)       | (0.0473)       | (0.0528)       | (0.0527)       | (0.0526)       |
| \(\rho\)      | 0.9396***      | 0.9413***      | 0.9369***      | 0.9633***      | 0.9627***      | 0.9633***      | 0.8345***      | 0.8325***      | 0.8381***      |
|                | (0.0085)       | (0.0084)       | (0.0087)       | (0.0053)       | (0.0054)       | (0.0053)       | (0.0172)       | (0.0175)       | (0.0171)       |
| GDP            | 4.0793***      | 3.2598***      |                | 0.8750         | -0.4251        |                | 0.2148***      | 0.2255***      |                |
|                | (0.8616)       | (0.8939)       |                | (1.8218)       | (1.8897)       |                | (0.0529)       | (0.0562)       |                |
| Politic        | 1.6600         | -0.2991        | 0.1259         | -16.3138**     | -20.0163**     | -15.6141**     | -0.6477**      | -0.6188*       | -0.8656***     |
|                | (3.3941)       | (3.5354)       | (3.4475)       | (6.1729)       | (6.5182)       | (6.1864)       | (0.3209)       | (0.3342)       | (0.3259)       |
| Indebtedness   | 1.1103**       | 1.1902**       |                | -0.3487        | -0.3167        |                | 0.0246         | 0.0293         |                |
|                | (0.4848)       | (0.4896)       |                | (0.9527)       | (0.9562)       |                | (0.0346)       | (0.0353)       |                |
| Indebtedness\(^2\) | -0.0074**    | -0.0079**      |                | 0.0049         | 0.0045         | -0.0003        | -0.0003        | -0.0003        |                |
|                | (0.0037)       | (0.0038)       |                | (0.0073)       | (0.0074)       |                | (0.0003)       | (0.0003)       |                |
| Density        | -0.0247        | -0.0116        | 0.0347         | -0.0157        | -0.0111        | 0.0049         | -0.0046**      | -0.0045**      | -0.0027        |
|                | (0.0313)       | (0.0322)       | (0.0307)       | (0.0741)       | (0.0748)       | (0.0735)       | (0.0017)       | (0.0017)       | (0.0017)       |
| Sunshine       | 0.5459         | 0.5790*        | 0.7937**       |                |                |                |                |                |                |
|                | (0.3460)       | (0.3432)       | (0.3498)       |                |                |                |                |                |                |
| Windspeed      |                |                |                | 0.1790         | 0.1905         | 0.1808         |                |                |                |
|                |                |                |                | (0.3408)       | (0.3451)       | (0.3401)       |                |                |                |
| AREA           | 0.0178***      | 0.0192***      | 0.0110***      | 0.0285***      | 0.0284***      | 0.0259***      | 0.0005**       | 0.0005**       | 0.0002         |
|                | (0.0042)       | (0.0043)       | (0.0040)       | (0.0100)       | (0.0099)       | (0.0096)       | (0.0002)       | (0.0002)       | (0.0002)       |
| South-East     | 27.5935        | 29.7739*       | 26.124         | -141.5067***   | -143.5835***   | -137.1818***   | -1.6025*       | -1.4891        | -1.9142**      |
|                | (17.3862)      | (17.4171)      | (17.5039)      | (41.3790)      | (40.9635)      | (42.0775)      | (0.9131)       | (0.9096)       | (0.9630)       |
| South-West     | 50.3074***     | 49.9457***     | 44.4153**      | -115.2488***   | -121.1718***   | -109.5811***   | -1.6050*       | -1.3682        | -2.2665**      |
|                | (17.1598)      | (17.2664)      | (17.8370)      | (40.8658)      | (40.5800)      | (42.5697)      | (0.9076)       | (0.9152)       | (0.9994)       |
| North-West     | 2.0187         | 11.9102        | -0.0138        | -47.9213       | -42.5618       | -47.3039       | -0.8897        | -0.9904        | -1.2093        |
|                | (17.8207)      | (17.9388)      | (17.5826)      | (42.6214)      | (42.2961)      | (42.6771)      | (0.9414)       | (0.9484)       | (0.9656)       |
| Oil price      | 0.0522         |                |                | 0.1126*        |                |                | -0.0021        |                |                |
|                | (0.0368)       |                |                | (0.0677)       |                |                | (0.0038)       |                |                |
| CO2            | -9.3297***     |                |                | -7.0963*       |                |                | 0.0876         |                |                |
|                | (2.1006)       |                |                | (3.9006)       |                |                | (0.1983)       |                |                |
| VA\(_{Ind}\)  |                | -0.7406        |                | 2.8382         |                |                | -0.1761*       |                |                |
|                |                | (1.5852)       |                | (3.2716)       |                |                | (0.1047)       |                |                |
| Constant       | -216.8007***   | -155.6054***   | -89.1553**     | -37.4155       | 59.0383        | -38.9524       | -5.0337**      | -6.1613*       | 5.5114**       |
|                | (42.1356)      | (50.8682)      | (36.1553)      | (93.0290)      | (107.0408)     | (78.9308)      | (2.4794)       | (3.4650)       | (2.2235)       |

Note: *\(p < 0.1\); **\(p < 0.05\); ***\(p < 0.01\); standard errors are shown in parentheses.
are positive and highly significant, varying from 0.1469*** to 0.1927*** if we take account the three closest neighbours, and from 0.1924*** to 0.2491*** for the four closest neighbours. For the five closest neighbours, the coefficient varies from 0.2302*** to 0.2855*** (see Tables A5 and A8 in the supplemental data online). These results confirm the existence of interdependence and considerable clustering of solar deployment. The departments seem to be interested in what their neighbours are doing in terms of solar energy production. Concerning the explanatory variables, the results are qualitatively unchanged.

The results for wind energy are also consistent with those obtained previously using the contiguity matrix. Indeed, the spatial lag parameters are positive and significant confirming the existence of spillover effects. For the bioenergy, the results (excepted the results obtained with the three closest neighbours matrix) also go in the direction of those obtained with the matrix of contiguity (see Tables A7 and A8 in the supplemental data online). Finally, regarding the explanatory variables, GDP, debt, sunshine and area of the department remain significant for solar energy, but it depends on the considered matrix. The surface area and political ideology of the department seem to be the only drivers of wind energy deployment. GDP is positively correlated to bioenergy deployment in addition to surface area.

Other determinants

In this section we estimate again the previous models by adding other potential determinants (CO2 per capita, oil price, VA_ind) of RE deployment (Table 6). The CO2 per capita variable is used as a proxy for environmental degradation (Marques et al., 2010), the value added of the regional industrial manufactory sector (VA_ind), normalized by GDP, is a proxy of the lobbying strength of the industrial sector, and the oil price is added to capture the substitution effect between fossil fuels and renewables.

The main conclusions are the following: (1) the results are close to those of Table A10 in the supplemental data online and the spatial lag coefficients are positive and highly significant for all considered RE sector; (2) the positive effect of debt on solar energy deployment is robust; and (3) the coefficients associated with the CO2 variable are negative and highly significant for solar and wind power. The coefficients associated with VA_ind are negative for solar and bioenergy, but they are not significant. With regard to oil prices, its effect is also not significant.

Thus, our results suggest that environmental concerns are not incentives to increase the solar and wind energies deployment in line with the previous literature (Marques et al., 2010). In other words, the amount of CO2 emitted is associated with a decrease in solar and wind deployment. The substitution effect is not verified. A small oil price increase does not seem to be enough to encourage the switch from grey to green power (Marques et al., 2010). The lobbying power of the manufacturing industry does not seem to disadvantage the local promotion of RE.

CONCLUSIONS

In a context of global warming, public policies and strategies encouraging implementation of clean energy technologies have been developed in most countries. France is no exception and has allocated economic and technical resources required to promote the deployment of RE sources. However, although the RE production targets were defined at the national level, establishing the means of production has largely been delegated to the local level, and particularly to the regional level (MEEDM, 2009). Thus, we go beyond the country level usually considered in the previous empirical literature to identify the drivers of RE deployment considering French data about ‘departments’. In addition, we consider proximity by explicitly taking account potential spillovers between local governments using spatial econometrics.

Several conclusions can be derived from this analysis. First, the spatial econometric analysis leads to the conclusion that the spatial model with serial correlation is the most relevant for describing the RE dynamics of French local governments. Second, spatial spillovers are significant and show the existence of proximity. Indeed, spatial dependence is highly significant for all RE sources (solar, wind, bioenergy), suggesting that the RE deployment in a given department is affected by neighbouring departments, especially for solar energy. Thus, a competition or imitation effect is likely to start between the local governments: environmentally conscious ‘departments’ are moving increasingly into green technologies and, not wanting to be overwhelmed by their neighbours, they invest in these technologies.

Third, we assess the potential drivers of RE deployment in French local governments. The GDP of a given department positively impacts the deployment of RE energy and that of neighbouring departments (income effect), except for the wind (specific constraints). High-income governments are more likely to support green technologies investments and RE deployment than low-income ones. RE deployment also depends on surface area and geographical factors. For example, solar energy is more highly developed in southern departments, while wind energy is more developed in the north. However, the natural conditions are not the only key to promote RE: for example, wind resource endowment is not a significant driver of wind energy deployment. In addition, regulatory constraints can be an obstacle to maximize the exploitation of natural resources such as wind speed. While the size of the economy is associated with increased RE deployment, the latter also has positive effects on economic growth and green job creation and public RE investments are strongly encouraged in France. In this context, indebtedness can be a mean to increase the income effect and generate RE deployment, job creation and future fiscal revenues. Financing infrastructure through indebtedness seems to be a way to help to promote RE deployment, especially in solar. However, the coefficient associated with CO2 is significantly negative, suggesting that environmental concerns are not incentives...
to increase the RE deployment. The oil price (substitution effect) and the value added of manufacturing sector (which uses oil and fossil fuels as an input and as a major driver of the activity) are not significant. Anecdottally, political ideology can be a determinant of RE deployment: right-wing governments seem to be more favourable to the development of wind and biomass energy, as seen in northern and eastern departments. Finally, we tested many interaction effects in order to test non-linear patterns, but we did not find any relevant results.

**DISCLOSURE STATEMENT**

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**NOTES**

1. For the Directive, see https://eur-lex.europa.eu/LexUriServ/LexUriServ.do?uri=OJ:L:2009:140:0016:0062:FR:PDF/.
2. Loi sur la transition énergétique pour la croissance verte, enacted in 2015
3. Schémas Régionaux Climat, Air, Énergie.
4. Plan climat–air–énergie territorial.
5. A total of €1 billion/year for R&D; 42% for new energy technologies.
6. We also conducted the same analysis at the regional level and derived similar results (available from the authors upon request). Although the RE deployment is organized by regions in cooperation with departments, we preferred to focus on the results with a better panel database (94 departments versus 18 greater regions) by maximizing econometric robustness. The limits in RE deployment of both local authorities (regions and departments) are exactly the same considering Article 88 from the French law of 12 July 2010 (Grenelle II).
7. See http://bilan-electrique-2017.rte-france.com/territoire-et-regions/le-solaire-en-region/.
8. For solar, it is large-scale PV systems; bioenergy here refers to agricultural biomass and biogas. There is a lot of missing data on food waste, so it was not taken into account in this study.
9. For the IEA’s 2017 World Energy Outlook, see https://www.iea.org/reports/world-energy-outlook-2017/.
10. Regulated by articles L.223-1 of the Monetary and Financial Code.
11. For more details on spatial analysis methods, see Buron and Fontaine (2018).
12. The Wooldridge test allows one to test for serial correlation in random- or fixed-effects one-way models derived by Wooldridge (2002) (for more details, see Drucker, 2003).
13. With an average of €31.5/kW installed on the transmission and distribution networks.

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