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Spatial factors influencing the territorial gaps of organic farming in France

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#### Abstract

The objective of the paper, from the municipality's organic farming ratio in France in 2019, is to determine the variables influencing their distribution over the territory. The identification of these variables may allows the development of organic agriculture. The influence of the neighbourhood externality on the distribution of organic farmers was tested by using a Spatial Durbin Model, and shows a strong spatial dependency of the phenomenon (between 0.51 and 0.74 depending on the size of the specified neighbourhood). The study also shows that the Areas facing natural or specific constraints payments (CAP subsidies) increase the probability of conversion to organic farming. Furthermore, the study shows that the protected designation of origin label has an ambiguous impact on the practice of organic farming. Indeed, the ratio is higher when the communes have a PDO for wine production, whereas the ratio is lower when the commune has a label for dairy production (cheese, cream or butter). Finally, we show that municipalities with agricultural land where yields are low (pedological constraint) and with an important share of forest have a higher organic farming ratio.

Keywords: Organic agriculture, Spatial distribution, Neighborhood effect, Soil

management, Common Agricultural Policy, European Green Deal

JEL classification: C21, Q18, R12

#### 1. Introduction

Organic agriculture is characterised as an alternative to intensive conventional agriculture. Yet in France organic agriculture is far from being the mainstream practice. In 2018, 9.5 % of French farmers were working organically on 8.5 % of the country's agricultural land (Agence Bio (2020)), far from meeting the demand for these products, forced to import 31 %. To develop the practice, the French government supported by the European Union, is setting up programmes to develop the practice, such as the "Ambition Bio" 2017 Program, with the aim of doubling the amount of organic land compared to 2013 by 2017 i.e. to reach 8% of the Utilised agricultural area (UAA, refers to the total amount of agricultural land). The objectives have not been achieved: in fact, only 6 percent of the UAA in 2017 were cultivated organically. At EU level, in 2020, a major plan of 1000 billion Euros has been implemented, EU Green Deal, with the objective of achieving carbon neutrality by 2050. The objectives set for the agricultural sector within this plan are to

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develop the practice of organic farming in the EU. In fact, by 2030, organic farming will have to represent 1/4 of the European UAA, as opposed to the current 8%.

In order to contribute to this objective, it seems legitimate to identify the factors that can explain the development of organic agriculture, with the aim of guiding policies especially in a spatial dimension.

Until the recent years, the literature dealing with this topic has mainly investigated the individual characteristics of farmers acting on the probability of conversion Padel (2001), Genius et al. (2006), Geniaux and Latruffe (2010): younger, more educated and environmentally sensitive farmers have a higher probability of conversion than other conventional farmers.

The development of organic agriculture is very heterogeneous depending on the territory. Out of 34259 communes in metropolitan France (excluding overseas territories) with at least one farmer, only 418 (1.2%) are 100% organic, and 52.4% of communes do not have an organic farmer. This observation forces us to question the role of municipalities in the development of organic agriculture to find out how the heterogeneity of the territories influences the development of organic farming.

The aim of this article is to understand how organic farmers are distributed on the French municipality. More precisely, this article looks at the spatial factors that explain the gaps in organic development between territories. Spatial factors influencing the distribution of organic farmers in a territory can be of different nature. Some of these factors have already been raised in the literature, the presence of many other organic farmers in a geographical unit pushing the farmer to convert Schmidtner et al. (2012), Bjørkhaug and Blekesaune (2013), this is called the neighborhood effect. The literature also shows the influence of the quality of the soil Wollni and Andersson (2014), Lampach et al. (2020) as well as the geographical organization of the activity and the distribution of the populations that also impacts the location of the various agricultural sectors Ben Arfa et al. (2009).

The influence of these factors will be tested to see if they also explain territorial organic development gaps in France, but they will also be supplemented by new ones, such as a proxy of the labor pool and the influence of Protected designation of origin (PDO) areas on the number of farmers in each commune. And finally we will study the influence of European subsidies, particularly Areas facing natural or specific constraints (ANC) payments, on the dynamics of municipal organic farming.

In the remainder of this article, we first justify, on the basis of previous studies, the inclusion of the different explanatory variables in the regression. Previous studies as well as new original justifications explain the link between these variables and the organic farming ratio of the municipality. Then in the third section we will address the econometric model to test the influence of neighbourhood geographical units, as well as the tests for the optimal choice of the specialisation of a *Spatial Durbin Model*.

#### 2. Spatial factors of organic conversion: an overview

The objective here is to understand the nature of heterogeneity between municipalities and its impact on the development of the organic farming sector. We will study three categories of factors of an exogenous nature to the decision of the municipality participating to increase the gaps in the development of organic agriculture between territories.

#### 2.1. Economic Geography

Geographic economics seeks to explain the geographical location of activities. According to Marshall (1890), then taken up by Krugmann (1991), firms will tend to agglomerate in a certain geographical area. This agglomeration allows gains of different kinds. First of all, this agglomeration allows the increased circulation of information allowing a knowledge and an easier use of new technologies, this endogenous sharing of knowledge brings growth for firms. This agglomeration also allows access to a large labour pool which appears optimal on both sides of the market. In fact, the firms are satisfied to be close to a workforce specialized in their fields of activity and in large quantities. And at the same time, the supply of labor by this strong demand for labor, sees its probability of finding a job increase. And finally, this agglomeration of activities, attracts suppliers upstream and downstream, therefore reducing transport costs. For Krugmann (1991) the location of agricultural sector is exogenous, while according to Daniel (2005),"If we pursue this reasoning by introducing a possible mobility of agricultural activities, agricultural production must be concentrated as close as possible [...] to the consumption basins." (p.535), this leads us to wonder whether Krugmann (1991) hypothesis of exogenous nature and non-mobility of farms is sustainable. The following elements show that the choice of location of the agricultural sector is endogenous in relation to different characteristics.

In their studies, Schmidtner et al. (2012), Bjørkhaug and Blekesaune (2013) show that the agglomeration of organic farmers in a given region allows faster development of the practice than in other regions with less organic farming. Indeed, Nyblom et al. (2003) notes that conventional farmers who have organic farmers in their neighbourhood have a higher probability of conversion than an isolated conventional farmer. According to Bjørkhaug and Blekesaune (2013), this effect exists because learning the practice of organic farming is based more on tacit than formal knowledge. The European specifications governing organic farming (Regulation (EC) No 834/2007) sets standards on products and production but does not explicitly gives the methods for achieving this, as this knowledge can be passed on by other farmers. Thus, proximity to an organic farmer increases the probability of accessing this tacit knowledge of farming practices, and therefore the probability of conversion.

Proximity to a large pool of skilled labour is also a characteristic valued by organic farmers. Indeed, Organic agriculture requires more work than conventional agriculture (2.41 annual work unit compared to 1.52 in conventional, Agence Bio (2020)). The practices required, by the specifications, based on a tillage greater need for additional labor. The manpower needed by the organic farmer, is a specialized workforce

in the agricultural field with general knowledge of agronomic principles to improve the productivity of the land in an environmentally friendly way.

Then, Daniel (2005) justifies the need for farmers to be close to consumers and processors by the fact that the cost of transporting agricultural goods is higher than teh one for manufactured goods. This is explained by the fact that agricultural goods most often require specific transport conditions (refrigerated transport, dairy tanker) while at the same time, as they are raw materials, the value per transported unit is low. Ben Arfa et al. (2009), completes the following remarks by indicating that "The more perishable the products are and the more frequently they are produced, the more the logistical aspect is the driving force behind geographical concentration" (p.813). Indeed, dairy farmers need a regular collection, not being able to store their production as the product is quickly perishable and collect at least twice a day. On their side, industrial milk processors have an interest to be located as close as possible to a concentration of dairy farmers in order to minimize collection costs.

Finally, for Krugmann (1991), the proximity of the urban centre is important in the choice of location. Indeed, if the firm is close to the city, it is closer to the consumers, which reduces transport costs. This is calls centripetal forces. However, at the same time activities will be moved away from the cities due to the strong competition for land, leading to a significant price difference per square meter between town and country, which he calls centrifugal forces. Schmidtner et al. (2012), that in the case of German organic farmers, the centrifugal forces are stronger, it indeed finds a positive impact with the distance from the centers of conurbations. However, in their study, Wollni and Andersson (2014) find that organic farmers are closer to the city (Marcala in Honduras in the studies) than conventional farmers. Organic farmers are more dependent on consumers than conventional farmers, who sell directly to consumers. So the former differ from the latter, seeking to be located closer to large cities, in order to reduce the cost of access to consumers. Agence Bio (2016), estimates that in 2015, 41% of organic farmers sold part of their production on the markets. In the same year, 36% of organic sales took place in markets.

#### 2.2. Public policy instruments contribute to the development of organic farming

In order to achieve their objectives, the public authorities have at their disposal more or less constraining instruments and more or less incentives. In France, agricultural policy is mainly played out at the supranational level by The European Common Agricultural Policy. Due to its heavy weight, 38% of the European Union's annual budget (56 billion in 2018), it influences the location of farms in general. Indeed, according to Daniel (2003), productions supported by market price support mechanisms (dairy, cereals) and other specific aids ("combined aid" for livestock farmers) are less geographically concentrated than other productions. We are going to mention two instruments, Protected Designation of Origin (PDO) areas and areas facing natural or specific constraints (ANC) payments, which participate or could participate in the development of organic agriculture in Europe, one of the main objectives of the Green Deal.

One of the instruments involved in influencing heterogeneity between territories is the designation of Protected Designation of Origin (PDO) areas. This geographical quality label informs the consumer that "whose quality or characteristics are essentially or exclusively due to a particular geographical environment with its inherent natural and human factors" article 5 of Regulation (EU) No 1151/2012. In fact, this label is awarded to municipalities located in a specific geographical area, so there are significant differences in the number of PDO per municipality (standard deviation = 2.96). These designations can influence the development of organic farming in a territory. Indeed, in order to produce under this designation, the operator must comply with the specifications associated with the product. Depending on the regulations, certain standards may echo the European organic regulation, particularly in terms of animal welfare (annual duration of pasture and natural diet). The question then arises as to whether this label is a substitute for the EU certified organic food label, or whether these two labels are complementary. For Allaire et al. (2015), the different PDO zones, separated according to the nature of the products (viticulture, cheese and others), all increase the likelihood of the commune having organic farmers. However, the wine-growing areas have a greater influence than the other two. Winegrowers are a profession that needs a quality label to be able to develop their production. Indeed, according to Avelin and al (2019), in 2018, 90.3% of the winegrowers marketed their production, so through the labels the producers can differentiate themselves from the others. This is why, according to Guittard (2020) 94% of the wines produced, i.e. 96% of the wine-growing areas in France have a label, of which 60% have the PDO label. While at the same time, concerning the PDOs for cheese production for example, the dairy farmer will seek less to differentiate himself from the others because most often (92%) he will sell his milk production in a long circuit (sale to food processing firms). Thus for the farmer the variable which will interest him will be the price at which he sells his milk. Concerning this variable, the price of milk, it appears that the price of organic milk in 2019 was sold on average 40% more expensive than conventional milk (461 euros/1000L in organic compared to 331 euros/1000L in conventional, according to Cazeneuve (2020)). Concerning the price of PDO milk, it varies according to the production regions linked to the production of the corresponding PDO cheeses. Thus, it appears that PDO milk from Franche Comté (French region) sells for an average of 5700 euros/1000L while PDO milk from Normandy is traded for 400 euros/1000L. Depending on the region of production, the PDO certification of milk production appears to be more profitable than the organic certification.

Another factor influencing the geographical location of organic farmers is financial support. Indeed, in the study by Latruffe et al. (2013), after 406 interviews with conventional farmers, she finds that the main factor that could enable the conversion of these farmers is the financial factor, such as an increase in subsidies for organic farmers. In this article we will focus on the Areas facing natural or specific constraints (ANC) payments. Created in 1976, this grant is the most important aid in terms of amounts funded by the European Agricultural Fund for Rural Development, co-financed by national organisations (state and regions) to the

level of 25%. In 2019, the 86226 French farmers eligible for this subsidy received an average of 12235 euros in ANC payments. The aim of this aid is to maintain agriculture in isolated areas or areas constrained by natural phenomena (mountains, poor quality soil). This makes it possible to maintain activity and social links in these regions. When it was created, 3 types of area could be eligible land, mountain areas, simple lessfavoured areas (land with low yields) and specific handicap areas<sup>2</sup>. These last two categories were reformed on 1 January 2019, by the application of the European regulation on rural development No 1305/2013, now called areas facing significant natural constraints and other areas affected by specific constraints. The areas facing significant natural constraints are areas constrained by biophysical elements defined in Annex 3 of the EU Regulation No 1305/2013, allowing for the harmonisation of areas at EU level. The second category, within the limit of 10% of the surface area of the Member State, is based on specific criteria specific to each country, which allows adaptation to agricultural and territorial particularities (in France, the criterion of fodder autonomy, extensive livestock farming, share of hedges). This classification as a constrained zone, which allows farmers (conventional and organic) cultivate in these areas to claim the ANC payments, also leads to heterogeneity between cities. According to Genius et al. (2006), this additional subsidy received by farmers reduces the fiscal pressure. This aid allows them to be less dependent on the income generated by their production, and thus they have lower incentive to choose high-yield agriculture as the aid already allows them to obtain a decent income. Thus, these farmers may be more inclined to change their practices, due to the presence of the ANC payments seen as a backstop.

#### 2.3. Quality soil influence

Finally, the territories differ in terms of their pedological and climatic characteristics. These characteristics influence the types of crops grown by farmers in order to maximise their production. As fertility is a complex indicator and composed of different dimensions, it is complicated to prioritize soil types according to their fertility.

How do these pedological and climatic heterogeneities influence the development of organic farming on the territories? Two articles (Lampach et al. (2020), Wollni and Andersson (2014)) provide a contradictory answer to this question. In its article, Lampach et al. (2020) finds that farmers in Phu-Tho province in Vietnam have a higher probability of conversion to organic than other farmers located in two other provinces. And Phu-Tho province happens to have the best climatic and pedological characteristics for agriculture. Thus, he concludes that farmers are more likely to convert when soil conditions are the most favorable. At the same time, Wollni and Andersson (2014) get that organic farmers are most often located in areas where the soil is of poor quality. Indeed, after studying a population of farmers operating in an area highly subject to erosive hazards, he find a greater share of organic farmers in the most constrained areas

<sup>&</sup>lt;sup>2</sup>Without specific criteria, political will having to be justified by "the maintenance of agricultural activity is necessary in order to ensure the maintenance of the natural space and their tourist vocation or for reasons of coastal protection"

compared to the rest of the study area. For him, there are two reasons for this result. First, as these areas are characterized by lower yields, the premium price of organic can help compensate for these yield losses and ensure an income for farmers. Moreover, organic practices can slow down soil erosion by improving soil structure (favouring fodder crops and winter cover to increase organic mass, avoiding deep ploughing). Thus, the farmer by a conversion to organic farming can improve these yields if he practices on soil is subject to erosion.

Finally, according to Power (2010), ecosystem services provided by natural ecosystems (in particular by the diversity of species), i.e pollination, biological pest control, maintenance of soil structure and fertility, are indispensable for the practice of agriculture. At the same time, the presence of forest and semi-natural elements <sup>3</sup> has an impact on species richness and diversity (Bengtsson et al. (2005), Rundlöf and Smith (2006), Le Roux et al. (2008)), an effect that can be amplified by biological practice (limiting pesticide use, crop diversity).

Thus, we can suspect the presence of a link between the presence of forests and semi natural elements on the conversion to organic farming. Indeed, as the presence of these natural elements improves the supply of ecosystem services, in particular pest control and soil fertility allowing a substitution of pesticides. And for Latruffe et al. (2013), technical obstacles, mainly disease management and pest control, are the main obstacles to conversion. Thus one can expect to find a higher ratio of organic farming in areas with dense forests and semi-natural elements as these make it easier to practice.

#### 2.4. Research question

The hypothesis developed in this article will deal with the influence of heterogeneity factors between municipalities on the density of organic farmers and based on the theoretical effects previously revealed.

**Hypothesis 1:** The density of organic farmers in the neighborhood of a municipality has a positive influence on the density of the commune observed.

This result implies a clustering phenomena in the distribution of organic producers. This result has already been demonstrated by Schmidtner et al. (2012), Bjørkhaug and Blekesaune (2013). The magnitude of the dependence parameter seems to depend on the geographic units studied and the characteristics of neighborhood matrix.

Hypothesis 2: The density of organic farm is stronger in proximity to suppliers and labor pool.

By these behaviors, the organic producers has easy access to labour market, and reduce transport cost.

**Hypothesis 3:** The organic farms are located close to the large cities.

<sup>&</sup>lt;sup>3</sup>According to Fleury (2011), these are intermediate areas (moors, wasteland, groves) that are neither cultivated nor forested. The important aspect of these elements is their continuity, their connection, allowing mobile species to change habitat and find food. Without these elements, the species would disappear in areas of intensive agriculture.

Agence Bio (2016) estimates that in 2015, 41% of organic farmers sold part of their production on the markets. In the same year, 36% of organic sales took place in markets. Thus Organic farmers are more dependent on consumers than conventional farmers. This fact pushes organic farmers seeking to be located closer to large cities, in order to reduce the cost of access to consumers.

**Hypothesis 4:** The number of protected designations of origin (PDO) of a municipality has a positive influence on the density of organic farmers in the municipality.

A farmer in order to be able to label these PDO products must not only necessary to be part of the PDO geographical area but also to comply with strict specifications that may have similarities with the specifications Regulation (EC) No. 889/2008. Thus, a conventional farmer respecting PDO specifications will have fewer practices to adapt to switch to organic farming, thus reducing conversion costs.

**Hypothesis 5:** Municipalities eligible for ANC payments have a higher density of organic farming than other municipalities.

Farmers in these municipalities can receive significant additional support, which according to Genius et al. (2006) allows them to be less dependent on the income generated by their production, and thus be more inclined to take the risk of converting to organic farming.

**Hypothesis 6:** The ratio of organic farmers is higher in areas where farming practice is constrained.

Indeed, the practice of organic farming can improve soil structure (slowing down erosion, regulating of soil Ph, etc...). Moreover, the organic practice makes it possible to sell the production more expensive and thus to reach a correct income for the farmer.

**Hypothesis 7:** The ratio of organic farmers in the municipality as well as in its neighbourhood, is positively influenced by the share of forest and semi-natural elements.

These elements allow the production of ecosystem services, which allow the substitution of fertilizers and pesticides, thus making the conversion to organic agriculture easier.

## 3. Methodology: Spatial regression models

In order to explain the distribution of organic farmers in France, we will specify a linear regression which will integrate spatial lagged variables allowing to capture the influence of the geographical area on the ratio of organic farmers, allowing to estimate in particular the magnitude of the spatial dependence parameter, i.e. the neighbourhood spillover effect.

#### 3.1. Model specification

In order to capture the spatial dependence and spatial lag influence in the data, i.e. how the explanatory variables of the neighbours and the ratio of organic farmers of the neighbours influence  $y_i$  we implement a Spatial Durbin model. According to LeSage and Pace (2009), the model is written in the matrix form:

$$y = \rho Wy + X\beta + WX\theta + \varepsilon$$

$$\varepsilon \sim N(0, \sigma^2 I_n)$$

Where y is a vector n x 1 referring to the number of organic farmers per municipality; X dimension matrix n x k referring to the explanatory variable associated with all observations,  $\rho$  is a scalar indicating the spatial lag of the model. Then  $\beta$  and  $\theta$ , are size vectors k x 1, model estimators.  $\epsilon$  of size n x 1 is an error vector following a normal law  $\epsilon \sim N(0, \sigma^2 I_n)$ . W is the weight matrix of size n x n defined as next subsection.

In order to test the presence of autocorrelation of errors in the data, i.e. that the neighbour error influences the dependent variable of the considered observation, we will model a Spatial Error Model, specified as follows (according to LeSage and Pace (2009)):

$$y = X\beta + u$$
$$u = \lambda W u + \varepsilon$$
$$\varepsilon \sim N(0, \sigma^2 I_n)$$

#### 3.2. Neighborhood matrix

There are two ways of identifying the neighbours of an observation. Firstly, one can characterize as neighbours of an observation, all the individuals sharing a common border with the observation considered, in this case a matrix of contiguity is formed. The second method to identify the neighbours of an individual is to proceed by the maximum distance. Indeed, after having calculated the distances between the different points (observations), one can decide either to characterise the closest nth observations as neighbours (k-contiguity matrix), or to determine a maximum distance (metric neighbourhood matrix), forming a radius of the neighbourhood of the observed municipality.

The choice of a neighbourhood matrix which takes account of the fact that individuals share a common border does not appear optimal, because the inhabitants of a city do not only have relations with the inhabitants of border cities. Moreover, in the papers of Schmidtner et al. (2012), Bjørkhaug and Blekesaune (2013), they respectively decide to specify 15 and 30km matrices at Schmidtner et al. (2012) and 50 km for Bjørkhaug and Blekesaune (2013). In this study we choose 4 specializations, with a radius of 10, 15, 20 and 50 km. Then the weights are normalized to 1 in line to facilitate calculations.

#### 3.3. Test and model validity

Before estimating our model, it is necessary to check whether the data show a significant influence of the vicinity on the municipality's organic farming ratio and then to characterise this influence, i.e. to determine through which variable the neighbourhood effect transits. To do this, we will proceed to 3 categories of tests, respectively allowing us to verify the presence of spatial autocorrelation in the data (Moran's Test) as well as to determine the nature of the spatial autocorrelation (Lagrange Multiplier Test and Common Factor Test).

In order to test for the presence of spatial autocorrelation in the data, i.e. the significant influence of observations in the neighbourhood of an observation under consideration, the Moran's test is carried out (Cliff and Ord J (1981)). Table 1 shows that for all 7 constructed neighbourhood matrices, the hypothesis of absence of spatial autocorrelation in the model is rejected at 0.1% level.

To determine the origin of the autocorrelation, we carry out the 4 tests of the Lagrange multiplier developed by Anselin (1988), Anselin et al. (1996). The tests Lagrange Multiplier and Robust Lagrange Multiplier Error, allow concluding under the null hypothesis, that the parameter  $\lambda=0$ , i.e. absence of spatial autocorrelation of the error term. And the tests Lagrange Multiplier and Robust Lagrange Multiplier Lag, allow to conclude under the null hypothesis, that the parameter  $\rho=0$ , i.e. absence of spatial dependency. Table 1 indicates the presence of the parameter  $\alpha$  and  $\rho$  in the different specializations by the rejection of the H0 hypothesis at the 0.1% level.

Finally, to decide, in our case when  $\lambda \neq 0$  and  $\rho \neq 0$ , which model to choose between a specialization Spatial Durbin Model and Spatial Error Model, we perform a test of the common factor hypothesis by the likelihood ratio developed by Burridge (1981). Indeed, and according to the paper of Le Gallo (2002), if  $\rho\beta + \theta = 0$ , then the expression of the Spatial Durbin Model (1) can be reduced in the form of a Spatial Error Model (2):

$$y = \rho W y + X \beta + W X \theta + \varepsilon$$
 with  $\varepsilon \sim N(0, \sigma^2 I_n)$  (1)

$$y = X\beta + u$$
 with  $u = \lambda W u + \varepsilon$  and  $\varepsilon \sim N(0, \sigma^2 I_n)$  (2)

Thus if the H0 hypothesis is accepted, model (1) can be reduced to model (2) and therefore the model to be estimated is a Spatial Error model. But if the null hypothesis is rejected, then model (1) can be reduced to a model (2) and the model to be estimated is a Spatial Durbin model.

Table 1, indicates that the null hypothesis of the common factor by the likelihood ratio is accepted (K-1 ddl) only for the specification with neighbourhood at 50km, so the Spatial Durbin Model appears the most optimal for the other three specifications.

	10km	$15 \mathrm{km}$	20km	$50 \mathrm{km}$
Moran test	98***	137***	171***	312***
LM Err	4712***	8317***	12314***	34333***
RLM Err	0.1	301***	1459***	20031***
LM lag	5084***	8452***	11305***	14817***
RLM Lag	371***	436***	450***	515***
Common factor	205***	141***	86***	10.3

Table 1: Diagnostic tests for spatial dependence

Reading note: The value below in the "Common Factor" column refers to the calculated statistic, knowing that if it is greater than  $\chi^2_{7ddl}(1-\alpha=0.999)=24.3$ , then we reject the null hypothesis.

Concerning the estimation of the coefficients of the model, the direct effects (is the impact of a change in the municipality studied on the organic farming ratio) and indirect effects (is the total spillover effect on the neighbourhood induced by the change in municipality studied), they are obtained by simulations of 1000 Monte-Carlo chains by Markov chains (LeSage (1997), LeSage and Pace (2009)) based on the distribution of coefficients obtained by the Spatial Durbin Model. This estimation method is used by Lapple and Kelley (2014) because it is more relevant than conventional estimation methods (estimation by the maximum likelihood method) for spatial econometric models.

# 4. Analysis of the determinants of the municipal organic farming ratio

#### 4.1. Data and variable construction

In order to test the validity of the hypotheses developed earlier, we have built a database of the 34,970 municipalities in metropolitan France (in 2019). For each observation, we have these GPS coordinates allowing us to calculate the distances between each geographical unit. We also have the number of organic farmers in the commune on 1 January 2019, and the total number of farmers per municipality in 2017, allowing us to construct the variable "the municipality's organic farming ratio", the dependent variable. To verify hypothesis H2 we first integrate the variable Nb\_employed\_farmers and Share\_employed\_farmers, referring respectively to the number of employed farmers as well as the share of employed farmers in the employed population of the commune. To validate the other part of the hypothesis, we integrate the number of processors and distributors notified to the French Organic Farming Agency by municipality, designated respectively Nb\_processor and Nb\_supplier. Then, we construct the variables Dist\_100 and Dist\_50, referring respectively to the distance, in km, between the town studied and a town of 100,000 or between 100,000 and 50,000 inhabitants. This allows us to determine the necessity or not for farmers to be close to towns (hypothesis 3).

To verify the influence of PDO areas on the distribution of organic farmers (Hypothesis 4), we integrate the number of products that can receive PDO certification per municipality,  $nb\_PDO$ . This data allows the construction of 4 variables,  $nb\_wine\_spirit\_PDO$ ,  $nb\_dairy\_PDO$ ,  $nb\_fruit\_vegetables\_PDO$  and  $nb\_livestock\_PDO$  referring respectively to the number of PDOs relative to alcohol production (mainly wine), dairy production (mainly cheese), production of certified fruit and vegetables, and production and processing of certified meat. Then, in order to confirm hypotheses number 5, we include the binary variable  $ANC\_post2019$  equal to 1 when the municipality was classified as eligible before the entry into force on 1 January 2019 of EU Regulation 1305/2013.

Finally, in order to test the impact of soil quality on the practice of organic farming, we integrate the

variable Constrained area constructed by Le Barth et al. (2018). This variable indicates the share of the agricultural area of the municipality which is constrained by at least one criterion defined in Annex 3 of the EU Regulation No 1305/2013. In this annex, the Parliament indicates 8 criteria (dryness, shallow rooting depth, poor chemical properties, steep slope, etc.) and 14 thresholds beyond which agricultural land is qualified as a constraint, i.e. its productivity is negatively impacted.

Finally, in order to verify the supposed role of the forest and semi natural elements, we integrate 3 variables. Firstly, *Share\_forest* refers to the share occupied by the forest and semi natural elements in the commune, obtained from the Corinne Land Cover 2018 database. Secondly, the variable *Dist\_Forest*, which refers to the distance from the nearest public forest. And, the variable *Natura2000*, indicating whether there is a Natura 2000 classified area in the municipality.

#### 4.2. Result

The table 2, lists all the possible specifications with inclusion of the neighbourhood around 10km (the spatial lag of each variable is reported in appendix 3 table 5). Models (1) and (3) allow us to judge whether or not it is necessary to separate to separate PDOs according to the type of agricultural sector (wine-growing, market gardening, animal husbandry, dairy). We do not retain the model (3), the positive influence of the variable Nb\_PDO hides part of the information. Indeed, model (1) shows a divergence of the influence according to the nature of the PDO labelled product, the regression shows a positive influence for PDOs of wine and fruit/vegetable production while the PDO zone relating to livestock and dairy products do not influence conversion.

Then, in order to avoid the problems of multicollinearity, we add separately the variables  $Nb\_processor$  and  $Nb\_supplier$  (respectively in models (1) and (2)). We choose to retain model (1) based on the minimisation of the AIC information criterion and the maximisation of likelihood. Model (4) tells us that, contrintuitively, organic farmers seek to move away from cities with more than 50,000 inhabitants, contrary to the result of Wollni and Andersson (2014). Concerning regressions (5) and (6), controlling for the proximity of an agricultural labour pool, it appears first of all that the share of agricultural employees in the active population of the municipality does not influence organic farming practice. While the number of agricultural employees is increasing, the number of agricultural workers in the commune is increasing the municipality's organic farming ratio. However, as this last variable is correlated with other variables relating to the size of the municipality, it is not included in the regression specified in the table 3. Finally, in order to capture the influence of forest and semi natural elements on the conversion we specified regressions (1), (7) and (8). It appears that the share of forest as well as the presence of Natura 2000 areas in the municipality have a positive influence on the ratio of organic farmers in the municipality and in the neighbouring municipalities. We choose to keep the variable  $Share\_forest$  available for a larger number of observations.

	10KM (1)	10KM (2)	10KM (3)	10KM (4)	10KM (5)	10KM (6)	10KM (7)	10KM (8)
(Intercept)	0.02***	0.02***	0.013***	0.03***	0.018***	0.019***	0.028***	0.026***
Direct effect	-							
Economic Geographic nb_processor nb_supplier Dist_100	0.006***	0.007***	0.006***	0.006*** 0.001**	0.006***	0.005***	0.005***	0.006***
Dist_50 Nb_employed_farmers share_employed_farmers				0.001***	0.008	0.0002***	0.013	
PDO nb_PDO nb_wine_spirirt_PDO nb_fruit_vegetables_PDO nb_livestock_PDO nb_dairy_PDO	0.002*** 0.017** 0.011 0.002	0.002*** 0.018*** 0.012 0.002	0.002***	0.002*** 0.017** 0.008 0.0011	0.002*** 0.017** 0.007 -0.002	0.002*** 0.016** 0.007 -0.001	0.002*** 0.015** 0.007 0.002	0.002*** 0.016** 0.01 0.002
ANC_post2019 Constrained area	0.015*** 0.0001**	0.014*** 0.0001**	0.015*** 0.0001**	0.012** 0.0001*	0.0037 0.0001**	0.0037 0.0001***	0.003 0.0001**	0.015*** 0.0001*
Forest/Protected area share_forest Dist_forest Natura2000	0.015*	0.014*	0.014*	0.011	0.018**	0.018**	0.001*	0.006**
ho	0.508***	0.513***	0.529***	0.506***	0.49***	0.49***	0.5***	0.496***
Nb Obs AIC Log Likelihood	34943 -31204 15621	34943 -31121 15579	34943 -31100 15563	34943 -31242 15644	30315 -28408 14225	31006 -28454 14248	31119 -28395 14218	31122 -28419 14230

Table 2: Results of different Spatial Durbin Model specification with a neighbourhood of 10Km

The table 3, based on the specification (1) of the table 2 takes the results of the OLS as well as the Spatial Durbin model with MCMC estimation for the 3 neighbourhood matrices. Firstly, a significant and positive effect of the spatial lag parameter ( $\rho$ ) can be observed. The spatial lag coefficient varies between 0.51 and 0.74, validating hypothesis 1. This indicates that the density of organic farmers in a municipality has a positive influence on the number of organic farmers in its neighbourhood. The coefficient 0.51 (model (2)) can be interpreted as follows: if the density average of organic farmers in the vicinity of a municipality increases by 10%, the number of organic farmers in the considered municipality will increase by 5.1%.

Secondly, in relation to the geographical proximity of organic farmers to suppliers, the results of the table 3 show a positive direct and indirect effect, i.e the establishment of an organic processing company increases the ratio of organic farmers in the municipality as well as in its neighbourhood. However, we can suspect a reverse causality. Indeed, one can think that a processing firm can incite nearby farmers to convert by offering them contracts if they convert. But also that the firm integrates the location of the organic farmers in its choice of installation in order to minimize transport costs.

The results of the table, 3, indicate that municipalities eligible for ANC payments before 2019 have a higher density of organic farmers. The amount of the subsidy, on average 12235 euros, allows farmers' incomes to depend less on their production and thus to envisage a change in practice. Morever, it appears that areas where agriculture is strongly constrained, according to EU Regulation No 1305/2013, have a higher ratio of organic farmers. Lastly, the proportion of forests and semi-natural elements in the municipality has an influence on the proportion of organic farmers in the municipality as well as in neighbouring municipalities.

		10km (1)			15km (2)		20km (3)		
Effect	Direct	Indirect	Total	Direct	Indirect	Total	Direct	Indirect	Total
Economic Geographic									
$nb\_processor$	0.006***	0.016***	0.022***	0.006***	0.026***	0.032***	0.006***	0.031***	0.037***
PDO									
nb_wine_spirirt_PDO	0.002***	0.006***	0.008***	0.002***	0.006***	0.008***	0.002***	0.007**	0.009***
nb_fruit_vegetables_PDO	0.017**	0.018*	0.035***	0.018***	0.011	0.03***	0.018***	0.01	0.028**
$nb\_livestock\_PDO$	0.011	-0.021*	-0.01*	0.004	-0.013	-0.009	0.004	-0.014	-0.01
nb_dairy_PDO	0.002	-0.013**	-0.011***	0.002	-0.014**	-0.012***	0.002	-0.015**	-0.013**
ANC									
ANC_post2019	0.015***	0.007	0.022***	0.013***	0.012	0.026***	0.014***	0.013	0.027**
-		0	0.0001	0.0001*	0		0.0001*	0	0.0001
	0.000		0.000			0.000			0.000
Forest/Protected area									
,	0.015*	0.109***	0.125***	0.02***	0.112***	0.132***	0.025***	0.114***	0.139***
	0.000	0.200	0.1_0			0.202	0.020	0	0.200
ρ		0.508***			0.647***			0.738***	
l l									
ANC ANC_post2019 Constrained_area  Forest/Protected area Share_forest   P Nb Obs AIC Log Likelihood	0.015*** 0.0001** 0.015*		0.022*** 0.0001 0.125***	0.013*** 0.0001* 0.02***		0.026*** 0.0001 0.132***	0.014*** 0.0001* 0.025***		0.000

Table 3: Decomposition of the effects for a 10, 15 and 20 Km neighborhood with MCMC estimation

#### 4.3. Discussion

In order to verify that organic farmers respond to different localization logics than conventional farmers, we have reported the results (see Appendix 3) of the SDM model in which this time the dependent variable corresponds to the number of conventional farmers in the commune. One result differs significantly is the influence of the forest and semi-natural elements on the dependent variable. Indeed, for all three specifications, the share occupied by the forest negatively impacts the number of conventional farmers in the municipality as well as in neighbouring municipalities. This result is explained by the fact that farmers are competing for land with forests, as more forest implies necessarily less arable land and thus lower numbers of farmers. On the other hand, organic farmers need the forest and semi-natural elements to guarantee their production, through the production of ecosystem services. It can also be noted that conventional farmers seem to favour the most productive agricultural land (negative influence of the variable *Constrained\_area* for models 2 and 3). As these farmers sell for less than the price of organic, they have to produce more to achieve a sufficient income.

#### 5. Conclusion

This article complements older studies on the determinants of the localisation to organic farming, focusing mainly on the characteristics of farmers and their farms. However, it appears that exogenous factors influence decisions on practices. The study that has just been conducted on the municipality's organic farming ratio has made it possible to highlight the important role of relations between farmers, European agricultural policy, the geographical distribution of activities, and soil quality.

Firstly, there is an agglomeration effect of organic farmers in some regions. This can be explained by the fact that some of the knowledge needed to practise organic farming is tacit and informal. This knowledge is mainly passed on from one farmer to another. We have also shown that certain determinants of the new geographical economy also help to explain the location of organic farmers (distance from urban centres and proximity to suppliers).

The impact of PDO areas varies according to the agricultural sector concerned. It appears that the PDOs for wine and fruits/vegetables allow for an increase in the number of organic farmers, while the geographical areas concerned by livestock products do not influence conversion. It would seem that, depending on the type of marketing circuit chosen, the PDO and organic labels are either substitutable when the farmer chooses a long distribution channels and complementary circuit when the sale is direct to the consumer.

It also appears that the subsidies contribute to the development of the organic sector even if they are not intended to do so. Indeed, the ANC payments, allow farmers to increase their income without increasing their yield, so they have lower incentive to engage in high-yield (intensive conventional) agriculture that is harmful to their health and the people around them (in conformity with Sautereau and Benoit (2016), exposure to pesticides increases the likelihood of developing a disease such as Parkinson's, prostate cancer

or other cancers). Conversion to organic farming is then a viable alternative for the farmer.

And finally, it appears that the practice of organic farming is more developed in areas where the agricultural land does not allow high yields. In these areas, the practice of organic agriculture has two advantages, firstly it allows to preserve the quality of the soil, allowing to maintain and even increase productivity (in case of drought according to Rodale Institute (2011)), and secondly it allows to increase the value of the production, thus compensating for the loss of yield due to the poor quality of the soil. In addition, the ecosystem services provided by forests and semi-natural elements seem to increase the development of organic agriculture.

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# 6. Appendix

#### 7

# 6.1. Appendix 2: Summary table of variables

Table 4: Descriptive statistics of the variables

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# 6.2. Appendix 3: Indirect effect Table 2

	10KM (1)	10KM (2)	10KM (3)	10KM (4)	10KM (5)	10KM (6)	10KM (7)	10KM (8)
Indirect effect	-					/		
Economic Geographic nb_processor nb_supplier	0.016***	0.026***	0.02***	0.017***	0.013***	0.017***	0.022***	0.021***
Dist_100 Dist_50 Nb_employed_farmers Share_employed_farmers		0.020		-0.001** -0.002***	0.015	-0.00004*		
PDO nb_PDO nb_wine_spirit_PDO nb_fruit_vegetables_PDO nb_livestock_PDO nb_dairy_PDO	0.006*** 0.018* -0.021* -0.013**	0.006*** 0.019* -0.021** -0.013**	0.002*	0.005*** 0.019** -0.012 -0.0102*	0.005*** 0.024*** -0.013 -0.006	0.005*** 0.024** -0.013 -0.007	0.007*** 0.038*** -0.015 -0.013**	0.006*** 0.036*** -0.018* -0.014***
ANC ANC_post2019 Constrained area	$0.007 \\ 0$	$0.006 \\ 0$	-0.003 0	$0.012 \\ 0$	0.0289*** 0	0.0306*** 0	0.04*** -0.0004***	0.025*** -0.0004***
Forest/Protected area Share_forest Dist_forest Natura2000	0.109***	0.112***	0.112***	0.118***	0.068***	0.067***	-0.001	0.026***
ho	0.508***	0.513***	0.529***	0.506***	0.49***	0.49***	0.5***	0.496***
Nb Obs AIC Log Likelihood	34943 -31204 15621	34943 -31121 15579	34943 -31100 15563	34943 -31242 15644	30315 $-28408$ $14225$	31006 -28454 14248	31119 -28395 14218	31122 -28419 14230

Table 5: Indirect effect table 2

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### 6.3. Appendix 3: Spatial Durbin Model, dependant variable: Number of conventional farmers

		10km (1)			15km (2)			20km (3)	
Effect	Direct	Indirect	Total	Direct	Indirect	Total	Direct	Indirect	Total
$\begin{array}{c} Economic \ Geographic \\ \text{nb\_processor} \end{array}$	1.429***	-1.789*	-0.359	1.36***	-3.633*	-2.273	1.293***	-5.055	-3.762
PDO nb_processor nb_wine_spirirt_PDO nb_fruit_vegetables_PDO nb_livestock_PDO nb_dairy_PDO	1.429*** 0.587*** 4.977*** 1.817*** 0.566*	-1.789* 0.534*** 2.069* -0.085 -0.348	-0.359 1.121*** 7.046*** 1.733** 0.217	1.36*** 0.635*** 3.841*** 0.633 0.384	-3.633* 0.587 4.664** 1.702 -0.23	-2.273 1.221*** 8.505*** 2.335* 0.155	1.293*** 0.658*** 3.225*** 0.074 0.244	-5.055 0.519 7.115** 3.211 0.34	-3.762 1.177* 10.34*** 3.285 0.585
$\begin{array}{c} ANC \\ ANC\_post2019 \\ Constrained\_area \end{array}$	0.715* -0.0058	$0.178 \\ 0.0071$	$0.893 \\ 0.0013$	0.518 -0.0071*	$0.445 \\ 0.0085$	$0.963 \\ 0.0013$	0.477 -0.0085**	$0.383 \\ 0.0168$	$0.86 \\ 0.0083$
Forest/Protected area Share_forest	-6.505***	-5.974***	-12.479***	-7.125***	-8.032**	-15.157***	-7.572***	-10.485*	-18.058***
ho		0.508***			0.88***			0.738***	
Nb Obs LM Err RLM Err LM Lag RLM lag FC Test		34943 39843*** 3959*** 35981*** 97*** 36.4***			34943 72826*** 15355*** 57649*** 178*** 35.9***			34943 107228*** 34173*** 73347*** 292*** 18.7*	

Table 6: Decomposition of the effects for a 10, 15 and 20Km neighborhood with MCMC estimation for conventionnal farmers determinants