Spatial factors that influence territorial gaps in organic farming in France

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Abstract

Starting from organic farming ratios of municipalities in France in 2019, the objective of this paper was to identify local conditions for the development of organic farming. We began by identifying four characteristics that explain the heterogeneous development of organic farming practices in France using a Spatial Durbin Model to control the spatial autocorrelation of organic practices. This study shows that the protected designation of origin label has some ambiguous impacts on practices (i.e., positive for wine labels and not significant for livestock labels). The proximity of a high demand for organic products, instrumentalised by the number of organic shops (Two-Stage Least Squares), influences organic farming. Also, municipalities with low quality land and a high share of forest participate in the development of organic farming.

Keywords: `Organic agriculture, Spatial distribution, Organic consumption, Common Agricultural Policy`

`JEL classification: C21, Q18, R12`

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1. Introduction

Organic farming (OF), is defined by the European Commission Regulation No. 834/2007 as farming that does not use chemical pesticides, fertilizers or GMOs (genetically modified organisms), and attempts to preserve the environment and to guarantee the well-being of animals. However, organic agriculture in France is far from being the mainstream practice. In 2018, 9.5% of French farmers were classified as organic farmers and organic land represented about 8.5% of the country's agricultural land (Agence Bio, 2020). These levels of OF in France mean that the supply is far from meeting the demand for organic products since 33.5% of organic products consumed in France are imported (Agence Bio, 2021). In order to reduce these imports and the pollution linked to this trade, the EU is trying to develop organic practices across its territory. Moreover, in its EU Green Deal launched in 2020, the EU announced a transition "towards a healthier and more sustainable food system" (European Parliament, 2020) characterized by agriculture that preserves biodiversity and the environment. To achieve this, the EU aims to have 25% of UAA (useful agricultural area) in OF by 2030, compared to the current 8%.

The development of organic farming in France is very heterogeneous over the territory. Out of 34,259 municipalities in metropolitan France (excluding overseas territories) with at least one farmer, only 418 (1.2%) are 100% organic, and 52.4% of municipalities do not have any organic farms. This observation forces us to place the analysis at the level of the municipality in order to determine how the heterogeneity of the territories influences the development of OF.

The aim of this article is to understand how organic farms are distributed among French municipalities by identifying the factors that may explain the heterogeneous development of OF. Until recently, the literature dealing with the determinants of the development of organic agriculture has mainly focused on the individual characteristics of farmers acting on the probability of conversion. The articles of Padel (2001), Genius et al. (2006), Geniaux et al. (2010) report that farmers who are young, who have a high level of education and who are environmentally sensitive have a higher probability of conversion than other conventional farmers (CF). This article addresses the spatial factors that could explain the gaps in organic development between territories. What are the local conditions, external to the farmer's decision that can support the development of organic farming practices?

Spatial factors are characteristics related to the territory, which can be of natural origin (soil characterstics) or the result of historical human activity in this territory (share of farmers, number of inhabitants in the municipality). In this article, we attempt to determine if spatial heterogeneities, i.e., divergences in some elements from one commune to another, influence the number of organic farmers. The aim is to identify the natural environments as well as the characteristics linked to human activity that are favourable to OF, making it possible to formulate public policy recommendations to reinforce these phenomena. Some of these issues have already been raised in the literature. Wollni and Andersson (2014), Lampach et al. (2019), showed that natural environments, especially soil quality, influenced the OF but the direction of this effect is ambiguous. Other papers have shown the influence of spatial heterogeneity related to human activity.

Schmidtner et al. (2012), Coinon (2022) show that the presence of other organic farms in a geographical unit influences other farmers in the geographical area to convert to OF. This is referred to as the neighbourhood effect.

The influence of these identified factors are tested here to see if they also explain territorial organic development gaps in France. In addition, we study the role of new variables related to EU policies such as the influence of protected designation of origin (PDO) areas and payments for areas facing natural or specific constraints (ANC), on the dynamics of municipal OF. Finally, we test the influence of the forests and semi-natural elements that are present in the municipality on the development of organic farms. The intention is motivate the transition to OF by the fact that these natural elements are essential to the practice of agriculture and especially to OF.

We also test the influence of the local demand for organic products on the OF ratio. The introduction of this variable allows us to observe the effect on the agricultural practices of farmers in the municipality, as well as to measure the spatial spillover effect, i.e., does this local demand affect farmers in other municipalities? In order to avoid problems of reverse causality between the demand and supply of organic products, we instrumentalise the number of organic shops per 1000 inhabitants, which is a proxy for the consumption of organic products. Based on the work of Lambotte et al. (2020) and Kesse-Guyot et al. (2013), we regress the number of shops in relation to the characteristics of the population that influence the consumption of organic products (high level of education, more intellectual professions, large city).

To investigate the influence of these spatial characteristics as well as the influence of the organic neighbourhood on the conversion, we proceed with an empirical strategy based on spatial econometric studies. After having formed four neighbourhood matrices, we specify a Spatial Durbin Model (LeSage and Pace, 2009) that is robust according to the Lagrange multiplier tests (Anselin, 1988, Anselin et al., 1996) and the common factor test of Burridge (1981). The results of our models show that certain actions such as varying the share of forest in a municipality influence the number of organic farmers in the neighbourhood up to a radius of 20 km.

2. Spatial factors of organic conversion: an overview

According to Marshall (1890), then developed by Krugman (1992), firms tend to agglomerate in a certain geographical area. This agglomeration allows gains of various types. First, it favours the circulation of information and the diffusion of new technologies, helping firms to grow. Second, this agglomeration also tends to guarantee access to a workforce specialised in their fields of activity and in large quantities. Finally, this agglomeration of activities tends to attract upstream and downstream suppliers, therefore reducing transport costs. For Krugman (1992) the location of the agricultural sector is exogenous. However, according to the paper of Daniel (2005), farmers' location choices are endogenously influenced by different local characteristics.

In this section, we will show that some spatial factors of the municipality can influence organic practices by making them easier or more profitable. We look at three categories of factors that differentiate municipalities from each other, which can impact their OF ratio. These categories are the variable revealed by the new geographical economy (Krugman, 1992), as well as the differences related to European policy and, finally, the differences in the quality and use of the land.

2.1. Agricultural geographical economy

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

According to Daniel (2005), it is necessary for farmers to be close to consumers and processors since the transport cost of agricultural products is higher than for manufactured products. Indeed, given that agricultural goods most often require specific transport conditions (refrigerated transport, dairy tankers), while being raw materials at the same time, the value per transported unit is quite low. For example, dairy farmers require that their products be collected at least twice a day since they are not able to store their output due to its perishable nature. Thus, the location of farmers can be influenced by the proximity of downstream businesses.

Concerning the link between urban centres and organic farming, causality depends on the article. According to Schmidtner et al. (2012)who studied OF in Germany, organic farms are moving away from the city centres. However in their study, Wollni and Andersson (2014) found that organic farms are closer to the city (Marcala in Honduras in the studies) than conventional farms. This position allows them to be closer to consumers, reducing transport costs. This is due to the fact that organic farmers are more dependent on consumers than conventional farmers since their products are sold directly to consumers. Moreover, in France, Agence Bio (2016), estimated that in 2015, 41% of organic farmers sold part of their production on the marketplace. OF will therefore seek to move closer to major cities in order to reduce the cost of access to consumers.

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

In order to achieve their objectives, the public authorities can make some regulation and incentive policies. In France, agricultural policy is mainly played out at the supra-national level by the European Common Agricultural Policy (CAP). Due to its heavy weight (38% of the EU's annual budget), the CAP influences the location of farms in general. Indeed, according to Daniel (2003), crops supported by market price support mechanisms (dairy, cereals) and other specific aids ("combined aid" for livestock farmers) are less geographically concentrated than other crops. There are two instruments: Protected Designation of Origin (PDO) areas, and payments for areas facing natural or specific constraints (ANC), which can participate in the development of organic agriculture in Europe, one of the main objectives of the Green Deal.

Protected Designation of Origin

This geographical quality label identifies a product "whose quality or characteristics are essentially or exclusively due to a particular geographical environment with its inherent natural and human factors" [1]. In fact, this label is awarded to municipalities located in a specific geographical area, so there are significant differences in the number of PDOs per municipality (standard deviation = 2.96). These designations can influence the development of OF in a territory. Indeed, in order to produce under a PDO label, the farmer must comply with the specifications associated with the product. Depending on the regulations, certain standards may reflect European organic regulations, 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 (wine, cheese and others), increase the likelihood of the municipality having OF. Wine-growing areas have, however, a greater influence than the other two. Winegrowers are part of a profession that needs a quality label to be able to develop their production. Indeed, according to Avelin and al (2019), 90.3% of the winegrowers marketed their production in 2018. Thanks to the labels, producers can differentiate themselves from the others. This is why, according to Guittard (2020), 96% of the wine-growing areas in France have a label (60% of which are PDO labels). However, concerning cheese production, dairy farmers seek less to differentiate themselves from the others because most often (92% of the dairy farmers), they sell their milk production in a long circuit. These farmers will seek to obtain the label that allows them to better value their production. On the one hand, the price of organic milk in France is 40% higher than conventional milk (i.e., 461 euros/1000 L in 2019, according to Cazeneuve (2020)). On the other hand, there are differences in the selling price of PDO milk. Indeed, PDO milk from the *Franche Comté* region sells for 570 euro/1000 L (24% more than

[1] Article 5 of Regulation (EU) No 1151/2012

organic milk), whereas PDO milk from the Normandy region sells for 400 euros/1000 L (23% less than the price of organic milk). Thus, the effect of dairy PDOs on OF practices may be ambiguous depending on the territory.

Areas facing natural or specific constraints

Another factor that influences the geographical location of OF is financial support. Indeed, in the study by Latruffe et al. (2013), after 406 interviews with CFs, they found that the main factor that could enable the conversion of these farmers was the financial determinant; an additional subsidy could therefore lead to conversion to OF.

In this article we focus on payments for areas facing natural or specific constraints (ANC). 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 86,226 French farmers eligible for this subsidy received an average of 12,235 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 helps to maintain activity and, therefore, social links in these regions. Since the reform on 1 January 2019[2] , there are three types of land areas that could be eligible, mountain areas, areas facing significant natural constraints, and other areas affected by specific constraints. The areas facing significant natural constraints are areas constrained by biophysical elements [3], allowing for the harmonisation of areas at the EU level. The second category, within the limit of 10% of the surface area of the Member State, is based on criteria specific to each country, which allows adaptation to agricultural and territorial particularities (in France, these criteria include fodder autonomy, extensive livestock farming, share of hedges).

Thus, farmers operating in classified municipalities can claim ANC aid. This classification creates differences in the amount of subsidies received by farmers depending on the area of activity. According to Genius et al. (2006), this additional subsidy received by farmers reduces fiscal pressure. This aid allows them to be less dependent on the income generated by their production. Consequently, they have less incentive to choose high-yield agriculture since this aid already allows them to obtain a decent income. Thus, these farmers may be more inclined to change their practices due to the existence of ANC payments that serve as a guarantee.

[2]By the application of the European regulation on rural development No 1305/2013
[3]Defined in Annex 3 of the EU Regulation No 1305/2013

2.3. Quality soil influence

How do these pedological and climatic heterogeneities influence the development of OF in the territories? Two articles (Lampach et al., 2019, Wollni and Andersson, 2014)provide a contradictory answer to this question. In their article, Lampach et al. (2019) found that farmers in Phu-Tho province in Vietnam have a higher probability of conversion to organic farming than other farmers located in two other provinces, and that Phu-Tho province happens to have the best climatic and pedological characteristics for agriculture. He thus concludes that farmers are more likely to convert when soil conditions are the most favourable. At the same time, Wollni and Andersson (2014) report that organic farms 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, they found a greater share of organic farms in the most constrained areas compared to the rest of the study area. For them, there are two reasons for this result. First, since these areas are characterised by lower yields, the premium price of organic products 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, via the conversion to organic farming, the farmer can improve these yields if he farms on soil subject to erosion.

The quality of ecosystems surrounding agricultural land is also important. Indeed, according to Power (2010), ecosystem services provided by natural ecosystems, i.e., pollination, biological pest control, maintenance of soil structure and fertility, are indispensable for agriculture. Indeed, the presence of forests and semi-natural elements [4] has an impact on the quantity and quality of ecosystem services (Bengtsson et al., 2005, Rundlöf and Smith, 2006, Sautereau and Benoit, 2016).

Thus, we can suspect the presence of a link between the presence of forests and semi-natural elements on the conversion to OF. Indeed, the presence of these natural elements improves the supply of ecosystem services, in particular, pest control and soil fertility, thus allowing a substitution for pesticides. As for Latruffe et al. (2013), technical obstacles, mainly disease management and pest control, are the main obstacles to conversion. One can therefore expect to find a higher OF ratio in areas with dense forests and semi-natural elements since they are conducive to OF practices.

3. Methodology: Spatial regression models

In order to explain the distribution of OF in France, we specify a linear regression that incorporates neighbourhood-weighted spatial variables. This modelling allows us to capture the influence of the municipalities' characteristics on its OF ratio, as well as its impact on the neighbourhood.

[4] According to Fleury (2011), these are intermediate areas (hedges, 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.

3.1. Neighborhood matrix

First of all, before choosing the optimal spatial model, the neighbourhood matrix must be defined. This matrix, referred to as W, must represent the relationships between the different observations. In our case, Wi j ¿ 0 if farmers in the municipality have a relationship i with farmers in the municipality j; Wi j = 0 otherwise.

There are two ways of identifying the neighbours of an observation. Firstly, one can characterise all the individuals who share a common border with the observation considered as neighbours of an observation. 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 calculating the distances between the different points, a maximum distance is determined from which two observations are not considered as neighbours.

The choice of a neighbourhood matrix that takes account of the fact that individuals share a common border does not appear optimal since farmers in one municipality do not just have relations with farmers in border municipalities. Moreover, in the articles of Schmidtner et al. (2012), Bjørkhaug and Blekesaune (2013), they specify 15 and 30 km matrices, and 50 km, respectively. In this study, we chose four specializations, with a radius of 10, 15, 20 and 50 km. As for the weight of the relationship between i and j that allows us to judge the intensity of the relationship, we do not have enough information to assign a different weight. In this case, the sum of the weights of the neighbours of each municipality is normalized to 1.

3.2. Test and model validity

Before estimating our model, it is necessary to first check whether the data show a significant influence of the neighbourhood on the municipality's OF ratio, and to then characterise this influence, i.e., to determine through which variable the spatial effects transit. To do this, we carry out two categories of tests, the Moran test to test for the presence of spatial autocorrelation, followed by the Lagrange Multiplier Test and Common Factor Test to determine the nature of this autocorrelation.

Regarding the Moran test of Cliff and Ord (1981), the results of Table1 how that for all four constructed neighbourhood matrices, the hypothesis of absence of spatial autocorrelation in the model is rejected at the 0.1% level. These results can also be confirmed by a local analysis to detect the presence of clusters, according to the work of Anselin (1995). Local Moran's I allows the detection of two types of areas. When I_i is positive, it means that the municipality i has an OF ratio comparable to that of its neighbourhood. When I_i is negative, it means that the municipality i has an OF ratio opposite to that of its neighbourhood. The importance of the positive values (black zones) and the negative values (grey zones) on Figure 1 confirms the presence of a spatial autocorrelation.

To determine the origin of the autocorrelation, we carried out the four tests of the Lagrange multiplier developed by Anselin (1988) and Anselin et al. (1996). The tests (Lagrange Multiplier (LM Err) and Robust Lagrange Multiplier Error (RLM Err)) make it possible to conclude under the null hypothesis that

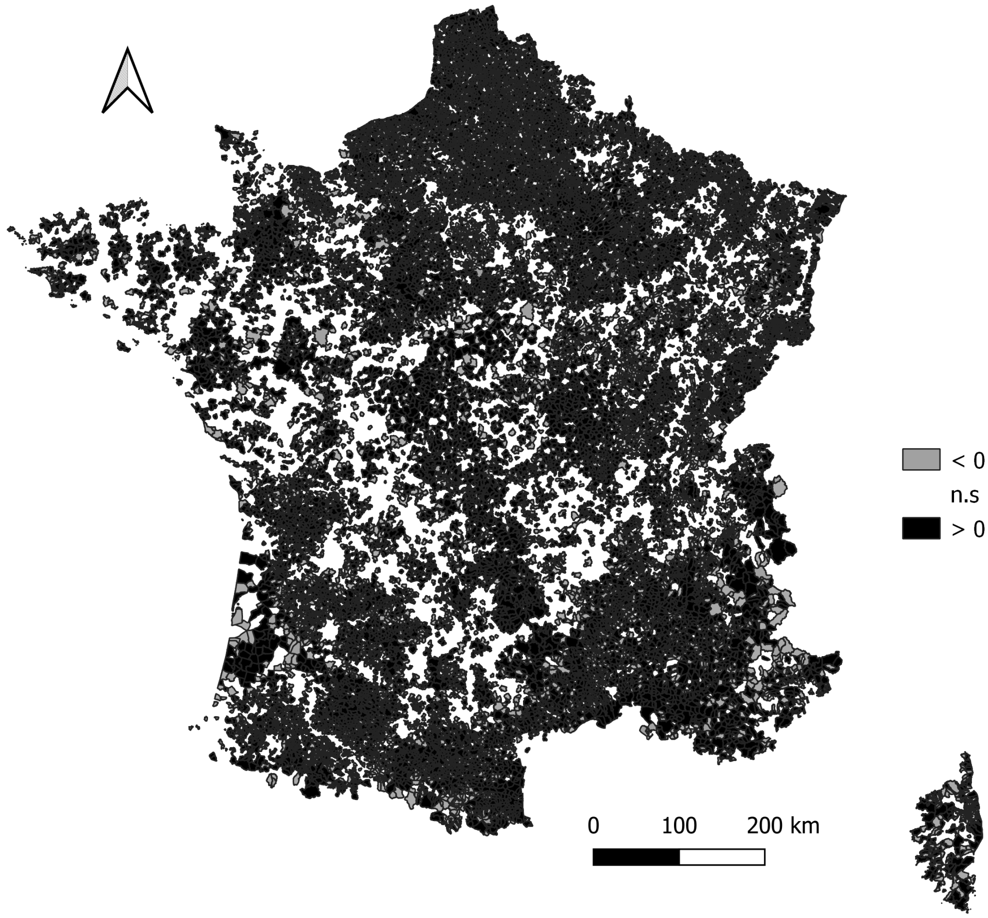

Figure 1: Local Moran's I for a neighbourhood matrix of 10 km

the parameter λ is equal to 0, i.e., absence of spatial autocorrelation of the error term. The Lagrange Multiplier (LM Lag) and Robust Lagrange Multiplier Lag (RLM Lag) tests allow us to conclude under the null hypothesis that the parameter ρ is equal to 0, i.e., absence of spatial dependency. Table1 indicates the presence of the parameters λ and ρ in the different specifications by the rejection of the H0 hypothesis at the 0.1% level.

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

$$y = \rho W y + X\beta + WX\theta + \varepsilon \qquad \varepsilon \sim N(0, \sigma^2 I_n) \tag{1}$$

$$
\begin{aligned}
y &= X\beta + u \\
u &= \lambda W u + \varepsilon
\end{aligned} \tag{2}
$$

Thus if the H0 hypothesis is accepted, model Eq.1 can be reduced to model Eq.2 and,therefore, the model to be estimated is a Spatial Error Model. However, if the null hypothesis is rejected, then model Eq.1 can be reduced to a model Eq.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 rejected (K-1 ddl) for the specifications with a neighbourhood up to 20km. It appears therefore that the Spatial Durbin Model is the most optimal (except for the 50km neighbourhood matrix).

	10km	15km	20km	50km
Moran test	95***	132***	165***	315***
LM Err	4577***	8158***	12131***	34247***
RLM Err	0.67	243***	1283***	19365***
LM lag	4953***	8357***	11314***	15403***
RLM Lag	377***	443***	466***	520***
Common factor[5]	***	***	***	

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 1: Diagnostic tests for spatial dependence

3.3. Model specification

Thus, on the basis of the tests previously carried out, the modelling of a Spatial Durbin Model that makes it possible to capture the spatial dependence and spatial lag influence in the data appears to be optimal. This modelling allows us to take account of the explanatory variables of the neighbours and the OF ratio of the neighbours influence y_i. According to LeSage and Pace (2009), the model is written in the matrix form:

$$
y = \rho W y + X\beta + W X\theta + \varepsilon \tag{3}
$$

Where y is a vector $n{*}1$ referring to the ratio of OF per municipality; X dimension matrix $n{*}k$ referring to the explanatory variable associated with all observations, ρ is a scalar indicating the spatial lag of the model. Then β and θ, are size vectors $k * 1$, respectively the OLS estimator and the lag dependence estimators. ϵ of size $n * n$ is an error vector following a normal law $\epsilon \sim N(0, \sigma^2 I_n)$. W is the weight matrix of defined size $n * n$.

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

Concerning the estimation of the coefficients of the model, the direct (impact of a change in the municipality studied on the OF ratio) and indirect (total spillover effect on the neighbourhood induced by the change in municipality studied) effects are obtained by simulations of 1000 Markov chain Monte Carlo (MCMC) samples (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 understand the spatial factors influencing the distribution of OF in France, we built a database of the 34,970 municipalities in metropolitan France. For each observation, we have the GPS coordinates that allow us to calculate the distances between each geographical unit. Les variables que nous allons ici cherché à expliquer sont la part de surfaces agricole biologique ainsi que le nombre d'agriculteur biologique de la commune. La première variable d'interet, repr\'ensente la part de surface exploité en agriculture biologique en 2019 dans la commune. Ceette variable est issu du traitement de Land Parcel Identification System (LPIS)[6] non anonnymisés, permettant de savoir au niveau de la parcelle ci elle est exploité en bio ou en conventionnelle. Nous retenons pour chaque commune sont emprise géographique. La base de données LPIS n'est pas exhaustif car elle inclus uniquement les agriculteurs recevant une aides de la Politique Agricole Commune. Pour completer cette indicateur nous calsulons aussi la part d'agriculteur bio dans la commune basé sur the number of organic farms in the municipality as of 1 January 2019 (from the Organic farmng Agency), and the total number of farmers per municipality in 2017 (from Agricultural Social Security called *MSA*), allowing us to construct the variable "the municipality's OF ratio"[7], the dependent variable. First, to verify the determinants revealed by the geographical economy, we integrate two types of control variables. To capture the presence of companies downstream of the sector, we integrate the variable *Organic shop* designating the number of distributors whose activity consists of selling organically-produced products. We also integrate two variables that characterise the position of the municipality in relation to large cities, 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.

[6] Established in France in accordance with in France in 2002 as the Land Parcel Identification System enforced by the European Council Regulation No 1593/ 2000

[7] Corresponding to the number of organic farms in the municipality divided by the number of farmers in the municipality.

To verify the influence of PDO areas on the distribution of OF, we integrate the number of products that can receive PDO certification per municipality, *Nb_PDO*. This data allows the construction of four variables, *Nb_wine_spirit_PDO*, *Nb_fruit_vegetables_PDO*, *Nb_livestock_PDO* and *Nb_dairy_PDO* ,referring, respectively, to the number of PDOs related to alcohol production (mainly wine), production of certified fruit and vegetables, production and processing of certified meat, and dairy production (mainly cheese).

Then, in order to test the impact of soil quality on OF practices, we integrate two types of variables. The first refers to soil quality and the other concerns the presence of forest and natural protected areas. So, to capture the soil quality, we include the variable *Constrained area* constructed by Terres et al. (2014). This variable indicates the share of the agricultural area of the municipality that is constrained by at least one criterion defined in Annex 3 of EU Regulation No. 1305/2013. In this annex, the Parliament indicates eight 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. In addition, in order to verify the role of the forest and semi-natural elements, we integrate the *Share_forest* and *Natura2000* variables. The first one refers to the share occupied by the forest and semi-natural elements in the municipality, obtained from the Corinne Land Cover 2018 database, and the second, Natura2000, indicates whether there is a Natura 2000 [8] classified area in the municipality.

Finally, in order to test the influence of European financial support on the OF ratio, we include the binary variable, *ANC_before_2019* equal to 1 when farmers in the municipality can receive ANC aid. We only take into account the municipalities already eligible before 1 January 2019. Indeed, EU Regulation No. 1305/2013 applies since that date. This regulation is based on the Terres et al. (2014) database, allowing the construction of the *Constrained area* variable. So as to avoid problems of multicolinearity between these two variables, we take into account the communes that were eligible for this aid before the introduction of this criteria. Table 5 (Appendix 1) shows the origin of each variable as well as the descriptive statistics of the variable.

4.2. Instrumental regression

In order to test the influence of the presence of organic consumers on the number of organic farmers, we integrate the number of organic shops in the municipality as a proxy. However, we suspect an inverse causality problem between the number of organic shops and the OF ratio. Indeed, it is possible to assume that a supplier firm can encourage nearby farmers to convert, for example, by offering them contracts that guarantee high purchase prices for the farmer, as well as the fact that the firm integrates the location of the organic farmers into its choice of installation in order to minimise transport costs. To tackle this issue, we use the method of instrumental variables in order to make the variable *Organic_shop* exogenous. Thus, the strategy

[8] A Natura 2000 area is an area made up of a group of natural land and marine sites. Its objective is to ensure the long-term survival of particularly vulnerable species and habitats with high conservation value in Europe.

is to explain the number of organic shops according to the characteristics of the population. Lambotte et al. (2020) and Kesse-Guyot et al. (2013) found that among regular consumers of organic agricultural products, people with a high level of education (Bachelor or Master's degree), holding a managerial position or having a higher intellectual profession (*Job_Cat3*) aand living in cities with more than 200,000 inhabitants are over-represented. Also, Lambotte et al. (2020), found that workers (*Job_Cat6*) are under-represented among regular consumers of organic products.

In the first stage, we regress the number of organic shops per municipality as presented in Eq.4. Where, Z_1 is the excluded instruments from the Lambotte et al. (2020) and Kesse-Guyot et al. (2013), X_2 corresponds to the instruments included i.e. also present in the second stage regression, Eq.5.

$$\widehat{X_1} = \gamma_0 + Z_1\gamma_1 + X_2\gamma_2 + \varepsilon \tag{4}$$

$$Y = \rho WY + \beta_0 + \widehat{X_1}\beta_1 + X_2\beta_2 + W\widehat{X_1}\theta_1 + WX_2\theta_2 + \varepsilon \tag{5}$$

	(1)	(2)	(3)	(4)
Excluded Instruments				
Bachelor Degree	-0.04	-0.02		
Master Degree	0.82***	0.68***		
City_200		34.39***		34.44***
Job Cat 3			0.96***	0.81***
Job Cat 6			-0.11*	-0.10*
Included Instruments				
Nb_wine_spirit_PDO	0.01***	0.01***	0.02***	0.02***
Nb_fruit_vegetables_PDO	0.17***	0.17***	0.17***	0.17***
Nb_livestock_PDO	0.01	0.01	0.02	0.01
Nb_dairy_PDO	-0.004	-0.001	-0.004	-0.001
ANC_before_2019	-0.11***	-0.10***	-0.11***	-0.10***
Constrained area	0.0004*	0.0004*	0.0004	0.0004
Share forest	-0.002***	-0.002***	-0.002***	-0.002***
Constant	0.10***	0.10***	0.17***	0.16***
Observations	33919	33919	33919	33919
Adjusted R^2	0.02	0.22	0.02	0.22
AIC	106599	98800	106647	98831
LogLik	-53289	-49388	-53312	-49404
Weak instrument	60***	88***	48***	55***
WU-Hausmann	82***	0.4	32***	0.04
Sargan	1.5	124***	42***	96***

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 2: First stage, Instrumental variable regression

In order to avoid problems of multicollinearity between the type of job and the level of education, we introduced them separately. The results of Specifications (1) to (4) of the table 2 corroborate with the articles of Lambotte et al. (2020), Kesse-Guyot et al. (2013). The model predicts that municipalities with more than 200,000 inhabitants will have more organic shops, as well as municipalities whose inhabitants have a Master's degreehold a managerial position, or have a higher intellectual profession, whereas a larger share of working class people among the inhabitants of the municipality reduces the number of organic shops.

Concerning the results of the tests, it first appears that the instruments are weak. Indeed, the R^2 of the specifications is weak, as verified by the rejection of the null hypothesis by the Fisher test in the first step (test of Sargan (1958)). The endogeneity test, WU-Hausmann test (Hausman, 1978), indicates that when the variable *City_200* is integrated (specification 2 and 4) the null hypothesis of endogeneity of the variable *Organic shop* is rejected. Whereas in specifications 1 and 3, the rejection of the null hypothesis indicates that the variable *Organic shop* is endogenous and that the instrumental regression method is therefore optimal. Finally, the rejection of the null hypothesis of the Sargan overidentification test (Sargan, 1958) for the first specification confirms the validity of this model of our instrumental variable. For the second step of the empirical strategy, the Spatial Durbin Model, we chose to instrumentalise the variable*Organic shop* by specification (1) of the table 2, so the Eq.3 becomes Eq.5.

4.3. Result

Table 3lists all the possible specifications with inclusion of the neighbourhood within a radius of 10 km (the spatial lag of each variable is reported in Appendix 3, Table6). These direct effects are equivalent to the 15 and 20km neighbourhood matrices and are therefore not reported in Table 3. Specifications (1-3-4) and (2) allow us to judge whether or not it is necessary to separate PDOs according to the type of agricultural sector (wine-growing, market gardening, animal husbandry, dairy). We did not retain Specification (2) since the positive influence of the variable*Nb_PDO* hides part of the information. Indeed, Regression (1-3-4) shows a divergence of the influence according to the nature of the PDO-labelled product; the regression shows a positive influence for wine and fruit/vegetable PDOs, whereas the PDO zone relating to livestock and dairy products does not influence conversion. The spatial spillover effects in Appendix 2 also show that the livestock areas (dairy and meat PDOs) negatively influence OF. When taking only the number of PDO labels without distinction into account, we can only observe a positive influence.

Specification (3) tells us that organic farms try to establish themselves away from big cities (more than 100,000 residents), as was already reported in the article of Schmidtner et al. (2012). Finally, in order to capture the influence of forests and semi-natural elements on the conversion, we specified Regressions (1) and (4). 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 OF ratio in the municipality and in the neighbouring municipalities. Indeed, the designation of a Natura 2000 area increases the ratio of organic farmers to total farmers in the municipality by 0.69%, and has a cumulative effect on the municipalities within a radius of 10 km of the area by 2.92%. We chose to keep the variable *Share_forest* based on the AIC and Log Likelihood criteria.

	10KM (1)	10KM (2)	10KM (3)	10KM (4)
Direct effect				
Economic Geographic				
IV_Organic_shop	5.38***	0.69***	0.68***	0.62***
Dist_50			0.03	
Dist_100			0.1**	
PDO				
Nb_PDO		0.21***		
Nb_wine_spirit_PDO	0.11*		0.2***	0.19***
Nb_fruit_vegetables_PDO	0.79		1.61**	1.55**
Nb_livestock_PDO	0.98		0.5	0.7
Nb_dairy_PDO	0.21		0.14	0.21
ANC				
ANC_before_2019	0.79.	0.23	0.07	0.26
Constrained area	0.01*	0.01**	0.01*	0.01**
Forest/Protected area				
Share_forest	0.03***	0.02**	0.01*	
Natura2000				0.69**
ρ	0.51***	0.53***	0.51***	0.54***
(Intercept)	-0.5	1.9***	3.3***	3.9***
Observations	33919	33919	33919	33919
AIC	282480	282580	282440	282590
Log Likelihood	-141223	-141276	-141199	-141272

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3: Results of different Spatial Durbin Model specifications with a neighbourhood of 10 km.

Table 4, based on specification (1) of Table 3 takes the results of the Spatial Durbin Model with MCMC estimation for the three neighbourhood matrices. First, we can note than an increase in the consumption of organic products (approximated here by the instrumental variable), has a positive influence on the OF ratio in the area. Indeed, this increase in consumption in the municipality increases the number of organic farms in the municipality as well as in neighbouring municipalities (positive indirect effect).

The inclusion of the municipality on the ANC list (areas facing natural or specific constraints) before 2019, which allowed farmers to receive an additional subsidy, has a positive impact on the municipality's OF ratio of about 1%. Moreover, according to EU Regulation No. 1305/2013, it appears that areas where agriculture is strongly constrained have a higher ratio of organic farms. Lastly, the proportion of forests and semi-natural elements in the municipality has an influence on the proportion of organic farms in the municipality as well as in neighbouring municipalities. It thus appears that dense forest areas encourage conversion to organic farming. An increase of the forest share in a municipality by 1% increases the OF ratio in the municipality by 0.03%. The increase in the forest share in a municipality also influences organic farmers in the neighbouring municipalities. Indeed, the OF ratio in the neighbourhood within a radius of 10 and 20 km increases by 0.15% and 0.19%, respectively.

Effect	10km (1) Direct	10km (1) Indirect	10km (1) Total	15km (2) Direct	15km (2) Indirect	15km (2) Total	20km (3) Direct	20km (3) Indirect	20km (3) Total
Economic Geographic									
IV_Organic_shop	5.38***	19.24***	24.66***	4.99***	27.8***	32.8***	5.05***	34.6***	39.65***
PDO									
nb_wine_spirirt_PDO	0.11*	0.29*	0.4***	0.14***	0.27	0.41*	0.17***	0.24***	0.41
nb_fruit_vegetables_PDO	0.79	-1.16	-0.38	0.96·	-3.03*	-2.07·	0.86.	-4.14.	-3.28·
nb_livestock_PDO	0.98	-2.27**	-1.27**	0.33	-1.67*	-1.34*	0.3	-1.78	-1.48·
nb_dairy_PDO	0.21	-1.06**	-0.85***	0.23	-1.09*	-0.86*	0.22	-1.12	-0.9·
ANC									
ANC_before_2019	0.79·	3.8***	4.6***	0.8·	4.9***	5.71***	1.02**	5.49**	6.51***
Constrained_area	0.01*	0	0.01	0.01*	0	0.01	0.01·	0·	0.01
Forest/Protected area									
Share_forest	0.03***	0.15***	0.18***	0.03***	0.17***	0.2***	0.04***	0.19***	0.23***
ρ		0.51***			0.65***			0.74***	
(Intercept)		-0.5			-1.2*			-1.4*	
Observations		33919			33919			33919	
AIC		282480			282150			282040	
Log Likelihood		-141223			-141055			-141003	

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 4: Decomposition of the effects for a 10, 15 and 20Km neighborhood with MCMC estimation

4.4. Discussion

In view of the results of this study, we can propose two recommendations to policy-makers in order to increase the development of OF. First, it would be desirable to make it compulsory to include environmental measures in PDO specifications. This measure would allow a convergence between PDO specifications and European organic specifications. Thus, the transaction costs of converting to organic farming (change of practices, lower yields, acquisition of new knowledge) for farmers in the PDO area would then be lower. These changes in practice necessary to meet the PDO standards increase the probability of conversion. Membership in a PDO could be considered as a gateway to OF.

Second, public policies aimed at increasing and restoring semi-natural elements must be maintained and amplified. These elements allow for a spatial spillover effect of OF development through easier substitution of pesticides and fertilizers. In the already existing "Green Payment" scheme, it is mandatory that 5% of the farmer's area be classified as an area of ecological interest (AEI), partly corresponding to semi-natural elements. Nevertheless, according to European Court of Auditors (2017),58% of the areas declared as areas of ecological interest are productive areas[9], limiting the production of ecosystem services. Thus, there are two possibilities to improve the system of areas of ecological interest: either(1) by increasing the minimum level of AEI required, knowing that, on average, European farmers in 2016 declared 9.3% of AEI, but leaving the possibility for farmers to have a mixture of productive and non-productive AEI; or (2) by maintaining the threshold at 5%, but counting only non-productive AEI.

[9] Area giving rise to an income from the sale of the crop. For example, farmers decide to grow legumes (lentils, chickpeas, peas) considered as AEI. However, since this land is tilled, the impact on biodiversity is more limited.

5. Conclusion

This article is a complement to older studies on the determinants of the localisation of OF, focusing mainly on the characteristics of farmers and their farms. However, it appears that exogenous factors influence decisions about practices. This study of OF ratios of municipalities has made it possible to highlight the important role of the geographical distribution of activities, European agricultural policy and natural environments.

First of all, there is an agglomeration effect of OF in some regions. This study has identified variables that partly explain the origin of this agglomeration effect. We highlighted the important spatial spillover effect of the demand for organic products as being instrumentalised by the number of organic shops per 1000 inhabitants, on the development of OF in the surrounding municipalities.

The spatial heterogeneity of OF is also explained by the differences in subsidies between farmers. Indeed, we found that the OF ratio was higher in the communes listed in the classification as eligible for ANC aid. 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 farms, whereas 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 substitutes when the farmer chooses a long distribution channel and complementary circuit when the sale is direct to the consumer.

Finally, it appears that organic farming practices are more developed in areas where the agricultural land does not allow high yields. In these areas, organic agriculture practices have two advantages. On the one hand, they make it possible to preserve the quality of the soil, maintaining and even increasing productivity (in the case of drought, according to the Rodale Institute (2011), Lotter et al. (2003)), and on the other, they make it possible to increase the value of the crop produced, 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

Appendix 1: Summary table of variables

Table 5: Descriptive statistics of the variables

Variable	Definition	Mean	Std. Dev	Min	Max	N	Source
Organic ratio	Density of organic producers per municipality	9.97	0.17	0	100	34943	Agence Bio/ Agricultural Social Security
Economic Geographic							
Diploma	Breakdown of the population by level of education[10]						INSEE
Job Category	Breakdown of the population by type of job[11]						INSEE
Organic_shop	Number of organic shops per municipality	0.17	1.22	0	111	34058	Agence Bio
City 200	City with more than 200,000 residents	0.0002	0.15	0	1	34085	INSEE
Min_dist_100	Min distance, in km, from a municipality of + 100,000 residents	71	42	0	328	34943	
Min_dist_50	Min distance, from a municipality of between 50,000 and 100,000 residents	86.4	48	0	230	34943	
PDO							
Nb_PDO	The number of PDOs a municipality has	1.693	2.96	0	70	34970	INAO
Nb_wine/spirit_PDO	Number of PDOs related to alcohol production	0.86	2.7	0	70	34970	INAO
Nb_fruit/vegetables_PDO	Number of PDOs related relative to certified fruit and vegetables	0.11	0.39	0	3	34970	INAO
Nb_livestock_PDO	Number of PDOs related to certified meat	0.14	0.49	0	3	34970	INAO
Nb_dairy_PDO	Number of PDOs related to dairy production	0.55	0.85	0	5	34970	INAO
ANC							
ANC_before_2019	Municipality classified as areas of natural or other specific constraints	0.4	0.49	0	1	34970	French Ministry
Constrained surface	Share of agricultural surface constrained by natural condition	39	30.3	0	100	34970	GIS Sol
Forest/Protected area							
Share_forest	Share of forest and semi natural areas in the municipality	27	26	0	100	34970	Corinne Land Cover
Natura2000	Presence of a Natura 2000 zone in the municipality	0.36	0.48	0	1	34970	Natura 2000

[10] 0= No diploma, 1= Completed primary school, 2= Completed middle school, 3= Completed technical secondary school, 4= Completed secondary school, 5= Bachelor degree, 6= Master degree

[11] 1= Farmer, 2= Artisan, small business owner, company managers, 3= Managers and higher intellectual profession, 4= Intermediate occupation(nurse, school teacher, sales people, accountant), 5= Employees, 6= Workers

Appendix 2: Indirect effect

	10KM (1)	10KM (2)	10KM (3)	10KM (4)
Indirect effect				
Economic Geographic				
IV_Organic_shop	19.18***	3.03***	2.31***	1.87***
Dist_50			-0.05	
Dist_100			-0.12***	
PDO				
Nb_PDO		0.27**		
Nb_wine_spirit_PDO	0.29*		0.61***	0.69***
Nb_fruit_vegetables_PDO	-1.11		2.65***	4.08***
Nb_livestock_PDO	-2.25**		-0.74	-1.46·
Nb_dairy_PDO	-1.07**		-1.21**	-1.43***
ANC				
ANC_before_2019	3.78***	0.47	1.89**	3.43***
Constrained area	0	0.02*	0	-0.03***
Forest/Protected area				
Share_forest	0.15***	0.12***	0.11***	
Natura2000				2.92***
Nb Obs	33919	33919	33919	33919
AIC	282480	282580	282440	282590
Log Likelihood	-141223	-141276	-141199	-141272

Table 6: Results of different Spatial Durbin Model specification with a neighbourhood of 10km, indirect effect