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Crop Production and Crop Diversity in France: A Spatial Analysis

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ABSTRACT

This paper aims to provide empirical evidence of the effect of crop diversity on crop production and spillover effect. Based on the estimation of production functions with spatial concerns on an original and rich dataset, results of the study suggest that crop diversity has a positive and significant effect on crop production. Its marginal contribution is substantial when rainfall is low in the agroecosystem. Furthermore, spatial dependence is a major issue and could be explained by topographic, climatic and agronomic constraints.

Contents

1. Introduction

After an initial period when the Common Agricultural Policy (CAP) was aimed at European food security and based on increasing agricultural productivity, the second pillar of the CAP introduced other objectives, including rural development and the production of goods which are sustainable and environmentally friendly (Bureau and Toyer, 2014). Nevertheless, the negative ecological impact of agricultural development constitutes one of the major criticisms of the CAP. Following public awareness and scientific-based evidence of the function of ecosystem services, the role of ecosystems in crop production has increasingly been a focus of interest.

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Ecosystem services are defined as "the conditions and processes through which natural ecosystems, and the species that make them up, sustain, and fulfill human life" (Daily, 1997, p. 6). They contribute to the essential ecological functions on which agriculture depends, including erosion control, sediment retention, soil formation, genetic resources, water regulation and supply (Costanza et al., 1997). They also offer a wide variety of aesthetic, recreational and cultural services to human welfare. As outlined by Gardiner et al. (2009), Kremen et al. (2004), Altieri (1999), ecosystems within agricultural lands could provide services of biological pest control and pollination, as well as improvement of soil fertility that may promote agricultural production.[1]

The link between biodiversity and ecosystem services remains confused in scientific literature and in national or regional ecosystem assessments. Biodiversity can be considered in many different ways: as a regulator of ecosystem processes, final ecosystem service or good (Mace et al., 2012). As complex as this relationship could be, many authors have shown that biodiversity contributes to determining the quantity, quality and reliability of ecosystem services (Harrison et al., 2014; Luck et al., 2009). We consider that biodiversity[2] is a pillar of ecosystem services as it constitutes the ecological underpinnings of service provision. It is often seen as a public good which means that individuals cannot be effectively excluded from use (non-excludable) and where use by one individual does not reduce availability to others (non-rivalrous). We focus here on a subset of biodiversity, a part produced by the agroecosystem: crop diversity. It refers to "all diversity within and among wild and domesticated crop species [...] and in many situations, provides the link between stress and loss of resilience" (Di Falco and Chavas, 2008, p. 83).

Hence, markets do not reflect the full social costs or benefits of biodiversity and their management may be complex. Nevertheless, biodiversity valuation can help scholars and policymakers deal with this market failure by assigning a monetary value that reflects the social importance of biodiversity. This could help in designing effective tools for their management. From an economic viewpoint, assessing the value of biodiversity may be done with a variety of valuation approaches (Barbier, 2007; De Groot et al., 2002; Farber et al., 2002; TEEB, 2010). In this study, we use the production function-based approach where we assume that crop diversity is an input in the production process of agricultural goods, which are themselves marketed, and we attempt to assess its contribution to agricultural production while accounting for spatial dependence. Furthermore, crop diversity could play an important role in ecosystem resilience. Resilience refers to an ecosystem's capacity to recover from disturbances or unexpected shocks and maintain its essential functions (Holling, 1986). In the agroecosystem, when rainfall is scarce, crop diversity can act as a catalyzer to agricultural production.

At farm scale, crop diversity tends to increase the yield of each crop, although its impact on overall production is likely to be negative and its effect on profit unclear (Davis et al., 2012; Deytieux et al., 2012; Iverson et al., 2014; Lechenet et al., 2014). One of the explanations for the yield effect is the synergy obtained by rotating crops on a given field (Carrouée et al., 2012; Doré et al., 2011). Brisson et al. (2010) explored the stagnation of wheat yield in France, distinguishing agronomic, environmental (climate) and economic factors. They concluded that the change in rotation and decrease of legumes in practices are involved in this stagnation. In another analysis of yield evolution at global level, Ray et al. (2012) suggested that in many countries an increase in the number of crops per cropping cycle or intercropping with other crops could increase net food supply and farmer incomes. However, to the best of our knowledge, there is very little research conducted at a national level and we do not know of any study in France which examines the effect of crop diversity on crop production. Another important shortcoming in the literature is the scarcity of studies which integrate spatial dependence in the analysis.

Spatial dependence of agricultural production may be spearheaded by agronomic, environmental and economic factors. Indeed, the cluster pattern of agricultural production may be explained by some natural, historical, socio-cultural and institutional factors. The choice of the spatial unit is crucial, but the choice of homogeneous agronomic areas does imply neither that all agronomic characteristics are controlled nor that these areas belong to the same supply or consultancy networks. In particular, farmers can be part of a large network and exchange information on agricultural practices that could improve their productivity. Thus, due to exchanges of information in the network, copy-catting and learning effect, the levels of agricultural production in an area may be influenced by those in neighboring areas. Therefore, not accounting for spatial dependence may bias the estimates and lead to erroneous policy recommendations. Hence, this paper contributes to existing knowledge by shedding some light on the effect of crop diversity on crop production in France with some significant spillover effects across neighborhood. From a policy perspective, a better understanding of the factors that may influence agricultural productivity could give more insight into how policymakers could intervene via some incentives to protect both agricultural lands and biodiversity.

The overall objective of the study is to examine the effects of crop diversity and other factors on agricultural production while accounting for spatial dependence. More specifically, we aim, via econometric tools, to measure the impact of crop diversity on major crop production (cereals, oilseeds and protein crops) in a given Small Agricultural Region[3] (SAR) and other contiguous SARs. Using a rich dataset constructed with matching methods that allow for analysis at a national level, results of the study suggest that crop diversity has a positive and significant effect on crop production and its marginal contribution is substantial when rainfall is low in the agroecosystem. More importantly, spatial dependence is not at odds with the data. Our results suggest that, holding all other things constant, a 1% increase of labor (capital) will lead to an increase in crop production of 0.20% (0.24%). Similarly, a 1% increase of fertilizer will yield an increase of 0.57% in crop production.

The paper is structured as follows. In Section 2, we review the literature on the relationship between crop production and crop diversity. Section 3 provides the econometric model and discusses the data while Section 4 presents the results of the study. We conclude the study in Section 5 with some policy recommendations.

2. Literature Review

The relevance of biodiversity in the provision of ecosystem services has been fully documented in the literature. Tilman et al. (2005) demonstrated that plant diversity (number of plant species added to plots) improves plant primary productivity. Reich et al. (2001) found that higher plant diversity leads to greater carbon (CO_2) storage in plants and lower levels of nitrate in ground waters. Hajjar et al. (2008) gave an exhaustive survey of the links between crop genetic diversity and ecosystem services such as: (i) pest and disease management, (ii) enhancement in pollination services and soil processes and (iii) providing continuous biomass cover, aid in carbon sequestration and prevention of soil erosion. The debate has focused on the principle mechanisms

[1] From the 2005 report of the Millennium Ecosystem Services (MA, 2005), there are four types of ecosystem services: provisioning services: products obtained from ecosystems (food, raw materials etc.), regulating services: benefits obtained from the regulation of ecosystem processes (pest and disease control, carbon sequestration, etc.), cultural services: intangible benefits individuals obtain from ecosystem recreation, and aesthetic experiences (ecotourism, use of nature for religious acts etc.) and lastly supporting services: the basis for the services of the other three categories.

[2] As defined by UNEP (1993), biodiversity is the "variability among living organisms from all sources, including terrestrial, marine, and other aquatic ecosystems and the ecological complexes of which these are a part: this includes diversity within species, between species, and of ecosystems".

[3] In France, the SAR is a zoning made up of various municipalities with homogeneous conditions in terms of agricultural systems, soil and climate.

that might explain this benefit of plant diversity. Two explanations are found in the existing literature: sampling and complementarity effects. The sampling effects are considered as increasing plant diversity will eventually increase the likelihood of some species to adapt well to some particular pedo-climatic conditions (Tilman et al., 2005). A second explanation known as complementarity effects are perceived when particular species perform better in the presence of others (Chavas and Di Falco, 2012; Loreau and Hector, 2001). This complementarity leads to a form of division of labor and a better collective exploitation of available resources such as soil mineral and light. This complementarity is also better apprehended under crop rotation and diversification schemes. Hence, they might help reduce pathogens and pests that often occur when one single crop is used. Furthermore, they add nutrients to the soil (some farmers rotate nitrogen-fixing crops such as legumes with non-fixing crops such as maize which need nitrates) and protect the soil against erosion. Farmers might then be less prone to use artificial fertilizers which impair biodiversity.

Most existing studies which explored the effect of crop diversity on agricultural production used a crop diversity index such as the Shannon, Margalef and Simpson indices[4] as a measure of crop diversity. Bonneuil et al. (2012) discussed the interests and the limits of these different indicators. By and large, they do not take into account all dimensions of genetic diversity, focusing on species richness and evenness of their proportional abundance. Population data from different plant and animal taxa are commonly used to measure biodiversity. Birds are very useful indicators of biodiversity since they provide regulative ecosystem services such as seed dispersal, pollination and predation/pest control (Civantos et al., 2012; Mäntylä et al., 2012). More generally, bird communities are considered as a good proxy of wildlife state for practical and scientific reasons (Gregory et al., 2005). Their ecology and taxonomy are well-resolved. They are responsive to environmental change on a moderate spatial and temporal scale. Since they are easily detected and censused, they are well suited for monitoring. Several long-term bird surveys exist such as the Pan-European Common Bird Monitoring Scheme applied in European countries.

The high nature value farmland (HNV) index is another proxy of biodiversity in rural areas. It is widely accepted by the European Commission but the data are scarce for many countries. HNV comprises the hot spots of biological diversity in rural areas, characterized by extensive farming practices. According to Andersen et al. (2003, p. 4), HNV farmland is described as: “those areas in Europe where agriculture is a major (usually the dominant) land use and where that agriculture supports or is associated with either a high species and habitat diversity or the presence of species of European conservation concern or both”.

Focusing on the determinants of farmers' choice of practices concerning genetic diversity in Pakistan, Heisey et al. (1997)'s study demonstrated a positive effect of crop diversity on wheat production. Smale et al. (2002, 2003) working on the spatial distribution of genetic diversity of wheat in Australia and China also concluded that there was a positive link.

Di Falco and Chavas (2008, 2009), Di Falco et al. (2010), Chavas and Di Falco (2012) used a production function to explore the effects of crop diversity on the agricultural production in varying contexts: (i) developed and developing countries (Italy and Ethiopia), (ii) at different spatial scales (farm and region) (iii) using different crop diversity indexes (Shannon, Margalef, count) and (iv) several econometric methods ranging from cross-sectional survey to panel data analysis. Though, the specification of the production function varies slightly, depending on the availability of the data, these studies share a common premise. In Table 1, the main features of these papers are summarized. They suggest that crop diversity is positively and significantly related with production. By interacting diversity and rainfall, the results indicate that diversity contributes to the production when the agroecosystem faces lower or scarce rainfall. It is worth stressing that Chavas and Di Falco's (2012) paper is different to some extent since the authors do not explicitly use a crop diversity index. They analyzed the interaction between different productions. Interaction term between barley and wheat was positive and statistically significant, implying the presence of positive interaction effects across crops. This finding highlights the presence of complementarity effect in the agroecosystem. Hence, each crop tends to have a positive effect on the marginal productivity of other crops.

3. Methods

3.1. Econometric Model

To assess the effect of crop diversity on major crop production, we start from a parametric production function where we consider crop diversity as an input and we control for spatial effects of agricultural production and the impact of other inputs. Furthermore, we investigate the effect of resilience benefit of crop diversity in the agroecosystem. Our literature review above questions the status of independent input of crop diversity. Indeed, crop diversity can be a result of complex interactions within agro-ecosystems and a positive impact may reflect the presence of synergy among different system components. The explanation of crop diversity is beyond the scope of this paper. Nevertheless, we consider this potential endogeneity problem.

Empirically, we use a spatial autoregressive model with spatial autoregressive disturbance. Thus, we explore the spatial processes generated by the Cliff and Ord (1973) type models. More specifically, in the right-hand-side (RHS) of our econometric model we include the weighted average of agricultural production observed for other cross-sectional units and spatial autocorrelation in the error term. Considering crop diversity as an input implies to discuss its possible endogeneity. As exposed above, crop diversity may impact crop production but is not independent of the production system. Hence, the estimated model is:

$$\begin{matrix} Q = B\alpha + \lambda MQ + X\beta + u \\ u = \rho Mu + e \end{matrix}, \tag{1}$$

where Q is the $n \times 1$ vector of observations of crop production. B is a $n \times p$ matrix of observations on p RHS endogenous variables. X is an $n \times k$ matrix of observations on k RHS exogenous variables such as labor, land, capital, fertilizer, rainfall and depth of the soil. M is $n \times n$ spatial weight matrix defined here as the five-nearest neighbors.[5] e is an $n \times 1$ vector of disturbances. MQ and Mu are $n \times 1$ vectors known as spatial lags of dependent variable and disturbances respectively. α, λ, β and ρ are parameters to be estimated. As outlined by Di Falco and Chavas (2008), the share of land to be allocated to the i-th species is a choice variable. Furthermore, there is a reverse causality between the crop production and weighted crop production. Thus, an OLS and a traditional instrumental variable (IV) estimator will lead to biased and inconsistent estimates.

In a compact form, Eq. (1) is written as:

$$\begin{matrix} Q = Z\delta + u \\ u = \rho Mu + e \end{matrix}, \tag{2}$$

where $Z = (B, X, MQ)$ and $\delta = (\alpha', \beta', \lambda')'$. Eq. (2) is estimated by a Generalized Spatial Two-stage Least Squares (GS2LS). We use the

[4] The Shannon index assumes that individuals are randomly drawn from a large community, and that all species are represented in the sample. It is the most widely used index. Conversely, the Simpson index takes into account the number of species present in a given area, as well as the abundance of each species and gives more weight to the more abundant species in a sample. The Margalef index measures the species richness of biodiversity by simply counting the number of different plant species in a given area.

[5] In the study, in order to make the analysis straightforward, we assume that the spatial weight matrix is the same in the error term and spatial lag of dependent variable as well. But, it is possible to specify different spatial weight matrices though it is not a current practice. As a standard practice, we row-standardize the spatial weight matrix. Furthermore, we carry out a sensitivity analysis by using another weighting scheme, such as the queen contiguity and Delaunay triangulation spatial matrices.

Table 1
Overview of papers on the link between productivity and crop diversity.

	Country	Scale	Crop diversity	Output	Inputs	Econometric methods	Instruments
Di Falco and Chavas (2008)	Italy	Eight regions in the South of Italy	Shannon index	Durum wheat	Land, labor, fertilizer, capital (machines and building), rainfall	GMM estimators on panel data over the period 1970–1993	Lagged values of crop production and biodiversity index are endogenous and instrumented by their past values
Di Falco and Chavas (2009)	Ethiopia	Farm level	Margalef index	Barley (mean, variance and skewness)	Land, labor, fertilizer, animal traction, rainfall and farm characteristics	3SLS estimators on cross-sectional data	Biodiversity is endogenous in all three moment-based specification of stochastic production function. The instruments are: distance from input supplier, distance from all-weather road, distance from the nearest market town, lagged values for fragmentation
Di Falco et al. (2010)	Ethiopia	Farm level	Count index (number of crops grown per farm)	Teff, Barley, Wheat	Land, labor, fertilizer, animal traction, rainfall and farm characteristics	Instrumental variable estimator on panel data over the period 2002–2005	Biodiversity is endogenous and its instruments are land tenure security, gender, distance between plots and the farm
Chavas and Di Falco (2012)	Ethiopia	Farm level		Teff, Barley, Wheat	Land, labor, fertilizer, animal traction, rainfall and farm characteristics	Instrumental variable estimator on farm survey conducted in 1999 and 2000	The instruments used for output variables are farm agroecological heterogeneity, land share under conservation measures and distance from the input supplier

GMM and IV approach suggested by Drukker et al. (2013) and Arraiz et al. (2010). The estimation procedure is an extension of the works of Kelejian and Prucha (1998, 1999, 2010). The estimation of Eq. (2) can be done in two steps. First, Eq. (2) is estimated with an IV using a set of instruments H. It is assumed that in addition to the exogenous covariates X in Eq. (2), excluded exogenous covariates X_e are included. Hence, if we define $A=(X,X_e)$, the instruments H are the linearly independent columns of:

$$(A, MA, \ldots\ldots\ldots, M^q A),$$

with this set of instruments and setting $q \le 2$, the 2SLS allows for the estimation of δ. The resulting residuals from the first step are used to estimate an initial consistent but inefficient ρ using a general moment procedure. The consistent estimate for ρ is used to construct a weighting matrix that is necessary to obtain the optimal GMM estimate of ρ in a second iteration. Second, a spatial Cochrane-Orcutt transformation is applied to have a transformed model:

$$Q(\rho) = Z(\rho)\delta + e \tag{3}$$

with $Q(\rho)=(I_n-\rho M)Q$ and $Z(\rho)=(I_n-\rho M)Z$. Eq. (3) is then estimated by a 2SLS. The obtained residuals are then used to estimate a consistent and efficient GMM estimator for ρ.[6]

An overarching question is how the excluded exogenous covariates X_e for crop diversity are defined. As we are working on an aggregated level, it is very difficult to find adequate X_e. These instruments must be correlated with the endogenous variables but uncorrelated with the error term. Furthermore, they must not directly influence crop production. Pastures, forests, semi-natural areas and wetlands are reservoirs of biodiversity. If the arable areas neighboring these land cover categories have their biological potential increased, the share of land cover categories can be assumed a suitable instrument of crop diversity, a tool to increase plant disease resistance. Land cover categories with high biodiversity potential were drawn from CORINE Land Cover 2006 dataset. Share of these categories in a total area was calculated at the SAR level. A second candidate as an instrument is the share of farms with farm's holder under 40 years at the SAR level, which is given by the French Agricultural census 2010. The underlying rationale is based on the hypothesis that young farmers are more inclined to adopt agroecological practices, such as culture rotation. Standard statistic tests were applied to test their validity.

As a robustness check, we provide another result by constructing internal instruments for biodiversity based on Lewbel (2012)'s strategy where identification relies on heteroscedasticity. More specifically, each endogenous variable is regressed on the T vector (T is a subset of the exogenous X vector included in the regression excluding the endogenous variables) and the vector of residuals $\xi_k (k=1,2)$ is retrieved. These estimated residuals are then used to create instruments as follows:

$$(T-\overline{T})'\xi_k \tag{4}$$

with $\overline{T}$ the expected mean of T. Identification only works if the error terms in the auxiliary regression (ξ_k) are heteroscedastic. We therefore use Breusch and Pagan (1979) test of heteroscedasticity to ensure that this identification condition holds in our data. Our estimation approach is similar to Millimet and Roy (2016) in a spatial context.

The last methodological point to be discussed is the choice to not estimate a Spatial Durbin model, ignoring MX variables. First, few papers deal with spatial spillover on agricultural production. In Yu et al. (2014)'s study, evaluating spatial variation in Turkish agriculture at province level, only labor used in a province has a negative impact on agricultural output in others provinces. Moreover, computed indirect effects are insignificant. Ulimwengu and Sanyal (2013), working on Sub-Saharan Africa agriculture, exhibit insignificant neighbors' inputs elasticities when they consider the 1961–2006 period and a very small neighbor' labor elasticity on the 1991–2006 sub-period. In both cases, regional concurrence for labor in labor intensive agricultures could explain this negative impact. The French crop production is far from this situation. In fact, focusing on the relationship between crop diversification and production, literature shows that the impact essentially goes through the soil: better use of soil by crop rotation, fewer pests, less erosion. For all these reasons, no spatial lags of explanatory variables MX are introduced.

3.2. Data

The Small Agricultural Region (SAR) appears as a spatial delineation of interest, thereby it ensures good data availability and offers a relatively fine spatial resolution. This historical zoning defines homogeneous units in terms of agricultural systems and natural conditions in particular soil and climate (Klaztmann, 1955). This spatial scale is used for the empirical analysis of crop production by economists (Mouysset, 2014) and ecologists (Teillard et al., 2012). There are 708 SARs in France not including Corsica. Regions with less than three farms specialized (at least 75% of the value of their production) in major crops (cereals, oilseeds and protein crops) are excluded from the initial sample. This

[6] It is possible that the coefficient of the spatially lagged dependent variable is not significant. Hence, for the sake of parsimony, researchers could keep results with spatially correlated errors without a spatially lagged dependent variable. In this case, the estimation is straightforward with $Z=(B,X)$, $\delta=(\alpha',\beta')'$ and H are the linearly independent columns of (A,MA).

and several missing values left us with 645 SARs to work with in this study.

Data availability is a limiting factor when describing the spatial distribution of major crop production and its drivers at a national level in France. Two main databases are used: the French Farm Accountancy Data Network (FADN) provides a broad set of agricultural microeconomic variables on a limited number of farms ($n = 7378$ farms in 2007) designed to reflect the heterogeneity of farming at the NUTS 2 level and the French Agricultural Social Security (FASS) dataset providing socioeconomic variables for almost all French farm holdings ($n = 3,650,532$ farms in 2008[7]) but not on production inputs. The challenge is to build coherent data on major crop production at an interesting spatial scale.

Some data such as land and labor, which are given by the FASS dataset, are available for all farms (i.e. representative at a SAR level) and other data, such as the values of major crop production, capital and fertilizers are only available for a limited number of farms which constitute the FADN sample. One way of solving this issue is to impute these data in the FASS dataset using a procedure based on matching techniques. First, farms common to both datasets are identified using the minimal distance computed on variables common in both datasets.[8] Thus, for these farms which constitute the treatment group, the values of indicators are transferred from the FADN dataset. These indicators need to be estimated for the other farms. We hypothesize that the more similar two farms are, the closer their values of the variable of interest will be. The procedure consists in identifying the nearest neighbors in the treatment group of non-matched farm holdings from the FASS dataset using Mahalonobis Distance Matching. This identification relies on (i) a matrix of Mahalanobis distance by region between farm holdings, based on economic and context variables and (ii) a threshold beyond which two farms are no more considered as neighbors. The variables used for the distance are chosen among a set of 57 variables as the most significant ones for the indicator to transfer for the region (NUTS 2) based on regressions using the treatment group. Finally, the indicators for non-matched farms are the result of an average of their nearest neighbors among treatment group weighted by their distance.

With regard to the measurement of crop diversity, the Shannon index is employed.[9] It is a metric of ecological diversity taking into account both species richness and evenness of their proportional abundance (for a review of ecological diversity measurements, see Magurran, 1988; Peet, 1974). We compute the Shannon index using the spatial distribution of crop species. At the SAR level, data used to calculate the proxy of our crop diversity were drawn from the 2007 French Land Parcel Identification System (LPIS) based on a detailed geospatial data of 25 groups of crops, distinguishing essentially bread wheat, rapeseed, corn, sunflower, other oilseeds, other protein crops and some industrial crops such as beet.[10]

Soil and climate variables are used to capture natural conditions that could affect crop production. Average annual rainfall over 30 years are drawn from the Municipal Climate Dataset based on Météo-France[11] data (Joly et al., 2010). The original data at the municipality level are aggregated at the SAR level by assigning the average values. Water holding capacity and soil depth approximate the soil quality. Based on >500.000 measurement points from the French soil database developed by INRA-Infosol unit (Jamagne et al., 1995), average values are computed at the SAR level.

Table 2 provides the summary statistics of the main variables.

4. Results and Discussion

4.1. Exploratory Analysis

Before presenting the results of the econometric models, we first examine the data by means of graphical tools observing the correlation between crop production and spatially weighted crop production. Fig. 1 shows the distribution of crop production across SARs, with darker colors representing higher values of crop production. As expected, the main crop regions (Paris Basin essentially for bread wheat and barley, South-West for maize) show the highest values. Spatial patterns are clearly visible and crop production is quite homogenous for nearby SARs. Furthermore, we carry out a test for spatial autocorrelation using the Moran's I statistics.[12] In Fig. 2, we plot the crop production in SAR i against its spatially lagged values. The Moran's I (0.486) is positive and significant at 1%, implying a significant positive spatial correlation between nearby SARs. Results of the study also suggest that there is positive relationship between crop production and crop diversity (correlation coefficient = 0.342, p-value = 0.000), implying a link between an increase of crop diversity and an increase of crop production. Hence, it is important to gauge this global spatial dependence via rigorous regression analysis.

4.2. Benchmark Results

We first start with the naive model (a-spatial model). Results displayed in Appendix A indicate a positive effect of crop diversity on major crop production as well as the ecological resilience of crop diversity to boost agricultural production when rainfall is scarce. As expected, inputs such as labor, capital, fertilizer, rainfall have the expected sign and a significant effect on crop production. Surprisingly, the coefficient of land is negative and significant. This seems to be an old riddle in development economics (Barrett, 1996; Barrett et al., 2010; Carletto et al., 2013; Sen, 1962). These results will be biased and inefficient if spatial effect is an issue. In Table 3, we provide our benchmark results.[13] Before getting to the heart of the matter, we first examine whether crop diversity, its interaction with rainfall and spatial lag of major crop production are considered endogenous to major crop production. The Durbin-Wu-Hausman test (χ^2-value = 27.731; p-value = 0.000) resoundingly confirm that they are endogenous. We investigate whether the instruments are highly correlated with the endogenous variables by using a more general approach based on Anderson-Rubin test. Results (F-value = 3.84, p-value = 0.00) confirm that the instrumented variables have a significant effect on the regressand. The Hansen J test (Hansen J statistic = 2.854, p-value = 0.583) indicates that our instruments are uncorrelated with the error term.

In Panel A (Table 3),[14] based on the assumption of homoscedasticity (constant error variance of e over space), results of our study suggest that crop diversity has a substantiate effect on crop production. Under stress (low rainfall), the agroecosystem may respond differently and crop diversity may act as a catalyzer of ecosystem productivity. Our results sustain this claim. The marginal contribution of crop diversity is

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7 We use the 2008 dataset which refers to the period 1st January 2007–1st January 2008.

8 Variables common to both datasets are the following: municipality, birth date of the manager, surface, legal form, type of farming.

9 The formula for the Shannon index is: $-\sum_{i=1}^{N} p_i \ln p_i$, where p_i is the planted area share of the i-th species in the dataset of interest.

10 To a lesser extent, some permanent crops (vineyards and orchards essentially) are also introduced.

11 French National Meteorological Service.

12 $I = \frac{\sum_i \sum_j m_{ij} x_i x_j}{\sum_i x_i^2}$, with x_i the crop production in SAR i measured as the deviation from the mean, x_j the crop production in SAR j and m_{ij} the matching elements of the row-standardized weight matrix M (five-nearest neighbors).

13 We estimate the model step-by-step starting with only crop diversity, then rainfall and the interaction between crop diversity and rainfall (Appendix B). Results reveal that crop diversity is most likely a strong driver of crop production in this ecosystem as compared to rainfall. Nevertheless, results displayed in Appendix B suffer from omitted covariates and this could erroneously inflate the coefficients of crop diversity.

14 We have estimated a SARAR model and found that the coefficient of the spatially lagged dependent variable is not significant.

Table 2
Summary statistics of variables.

Variables	Description	Mean	Min	Max
Q	Log of agricultural production. It is the total production of farms specialized in major crops expressed in values (euros).	15.621 (1.864)	11.418	19.994
Crop diversity	Log of Shannon index	0.933 (0.34)	−2.303	1.297
Land	Log of land for production. It is Utilized Agricultural Area expressed in 100 m^2.	12.520 (2.010)	6.873	16.856
Labor	Log of agricultural work unit.	3.929 (1.832)	−0.693	7.966
Capital	Log of expenditures in machinery and building expressed in values (euros).	15.434 (1.852)	7.676	19.594
Fertilizer	Log of fertilizer use expressed in values (euros)	12.961 (1.936)	7.533	17.575
Rain	Log of annual rainfall (mm)	6.764 (0.203)	6.323	7.466
Water holding capacity	Log of mean of the water holding capacity (mm)	4.879 (0.337)	3.743	5.547
Depth of soil	Log of mean of the soil depth (cm)	4.397 (0.267)	3.426	4.875

Notes: Standard deviations in parentheses.

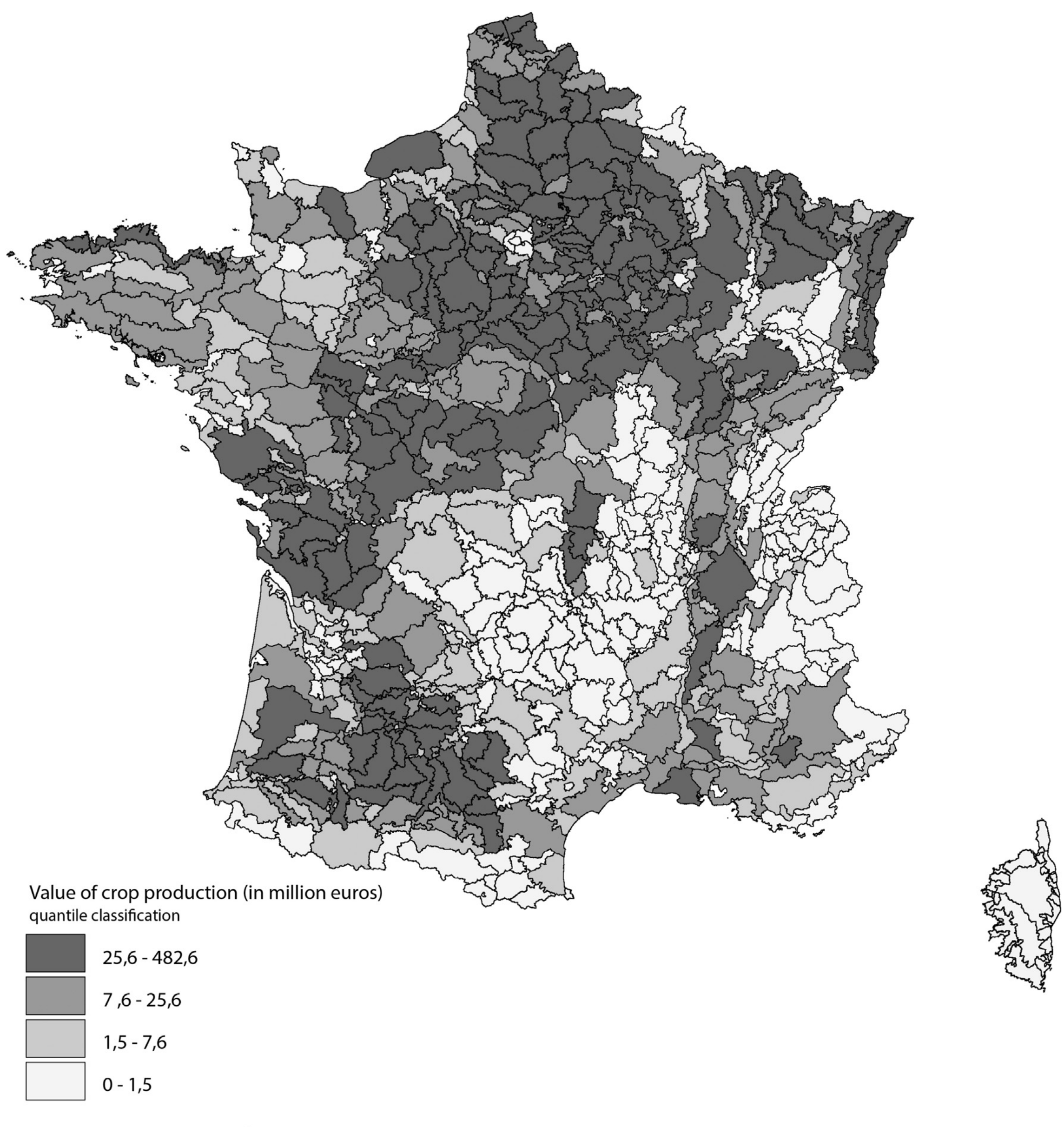

Fig. 1. Spatial distribution of agricultural production on major crops.

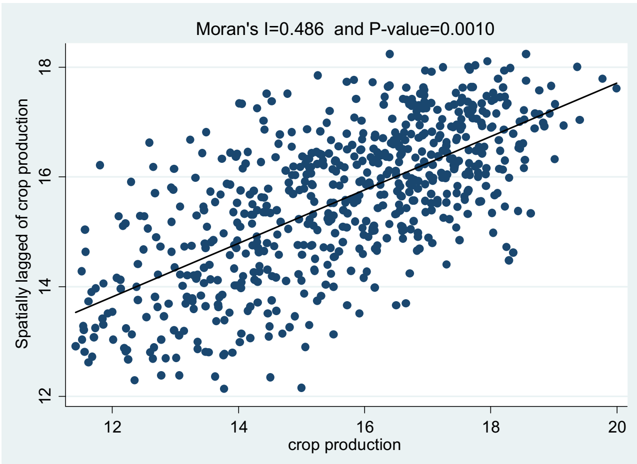

Fig. 2. Moran scatterplot for crop production (five-nearest neighbors).

stronger when the rainfall is low in the agroecosystem. This finding is consistent with Di Falco and Chavas (2008) and Di Falco et al. (2010). Regarding the measurement of crop production (total value of the production of specialized farms) and the measurement of crop diversity, we question the impact of cash crops, such as beets which increase diversity and act in the value of the total production. The weak correlation between the Shannon index and the industrial crops share (0.11) allows us to conclude that this relationship is not due to a cash crop effect.

Table 3
Spatial 2SLS estimation results (five-nearest neighbors).

Variables	Panel A	Panel B	Panel C	Panel D
Crop diversity	9.621***	9.593**	4.208***	4.161**
	(3.053)	(3.765)	(1.135)	(1.890)
Crop diversity × rain	−1.376***	−1.371**	−0.608***	−0.602**
	(0.429)	(0.534)	(0.159)	(0.266)
Land	−0.042	−0.043	−0.015	−0.016
	(0.031)	(0.057)	(0.025)	(0.058)
Labor	0.201***	0.202***	0.190***	0.192***
	(0.026)	(0.027)	(0.024)	(0.025)
Capital	0.240***	0.242	0.264***	0.266
	(0.030)	(0.169)	(0.026)	(0.164)
Fertilizer	0.568***	0.565***	0.534***	0.531***
	(0.031)	(0.111)	(0.026)	(0.103)
Rain	1.074***	1.072**	0.427***	0.420*
	(0.381)	(0.484)	(0.158)	(0.254)
Water holding capacity	0.111	0.111	0.145**	0.145*
	(0.078)	(0.086)	(0.071)	(0.079)
Depth of soil	−0.094	−0.094	−0.125	−0.125
	(0.096)	(0.097)	(0.089)	(0.087)
Intercept	−3.428	−3.410	0.916	0.972
	(2.622)	(3.241)	(1.155)	(1.772)
Spatial lag of error term	0.502***	0.467***	0.467***	0.436***
	(0.042)	(0.078)	(0.039)	(0.084)
N	645	645	645	645

Notes: Standard errors in parentheses. Panel A and B are the results of spatial 2SLS with homoscedasticity and heteroscedasticity with share of land with high biodiversity potential, share of farms with farm's holder under 40 years as instruments of crop diversity, respectively. Panel C and D are the results of spatial 2SLS with homoscedasticity and heteroscedasticity when we construct the internal instruments for crop diversity based on heteroscedasticity-based instruments, respectively. In all estimates, crop diversity and its interaction with rain and spatial lag of agricultural production are considered endogenous. *N* is the total number of observations. The spatial weight matrix used is the five-nearest neighbors.
* $p < 0.10$.
** $p < 0.05$.
*** $p < 0.01$.

Furthermore, labor, capital, fertilizer and annual rainfall have the expected positive and significant effect on crop production. Holding all other things constant, a 1% increase of labor (capital) will lead to an increase in crop production of 0.20% (0.24%). Similarly, a 1% increase of fertilizer will yield an increase of 0.57% in crop production.

Regarding the significance of the coefficient of the spatial effect ($\rho = 0.502$, p-value $= 0.000$), there is strong evidence for the clustering of crop production over space. This spatial effect is mostly explained by unobserved factors or shocks which is left unattended. As discussed previously, climatic, topographic and agronomic characteristics can be shared by neighbor SARs. Professional networks and local inter-connections between producers could also play.

So far, the results are based on the assumption that the error terms are homoscedastic. This assumption is unrealistic when dealing with spatial data since some cross units may have larger variances in larger areas. Hence, in Panel B of Table 3, we relax this assumption by accounting for heteroscedasticity[15] (Arraiz et al., 2010; Kelejian and Prucha, 2010). The effect of the resilience benefit of crop diversity in the agroecosystem and spatial dependence are confirmed. When accounting for space-varying error variance, the impact of other factors remains unchanged, nevertheless, the variance of all parameters substantially increases. In the case of the capital, the parameter is no longer significant.

In Panel C of Table 3, we report results of the study when we construct internal instruments following Lewbel (2012). This approach is based on the assumption of heteroscedasticity in the auxiliary equations and we first explore this assumption. In all cases, the Breusch-Pagan test rejects the null of homoscedasticity at the 1% level. We then examine whether endogeneity is a major issue in the study. The Durbin-Wu-Hausman test (χ^2-value $= 16.669$; p-value $= 0.000$) suggests that crop diversity, its interaction with rainfall and spatial lag of crop production are endogenous to crop production. The Anderson-Rubin test (F-value $= 1.59$, p-value $= 0.00$) confirms that the instruments have a significant effect on the endogenous variables. Furthermore, the Hansen J test (Hansen J statistic $= 12.837$, p-value $= 0.117$) reveals that our instruments are uncorrelated with the error term. To summarize, using this other set of instruments, our findings still confirm a positive effect of crop diversity on major crop production as well as the spatial dependence. Using internal instruments based on Lewbel's (2012) strategy, we can still have accurate results and this is consistent with other studies which have used this empirical strategy (Emran and Hou, 2013; Huang and Xie, 2013; Mallick, 2012).

Lastly, we probe our results by examining how different are the diversity effects considering low and high rainfall SARs. Thus, we create rainfall quintiles and define a variable which takes on the value 1 for the first two quintiles (low rainfall) and 0 for the two highest quintiles (high rainfall) and we run the estimation in the two sub-samples. Though there is a clear evidence for the clustering of crop production over space ($\rho = 0.4$ resp. $\rho = 0.6$; p-value $= 0.000$), the coefficients of crop biodiversity and the interaction of crop diversity with rainfall obtained have similar values and insignificant. Nevertheless, the variances are much higher in the estimation on the low rainfall areas foreshadowing less stable relationship when the agro-ecosystem face high water stress.

4.3. Sensitivity Analyses

Our main results above may be driven by the specification of the spatial weighting scheme. Hence, we consider alternative exogenous spatial links: a queen contiguity weight matrix (polygon contiguity) and Delaunay triangulation matrix. In the queen contiguity weight matrix it is assumed that two units are neighbors if they share the same common points (boundaries and vertices). With the Delaunay

[15] We use a parametric approach.

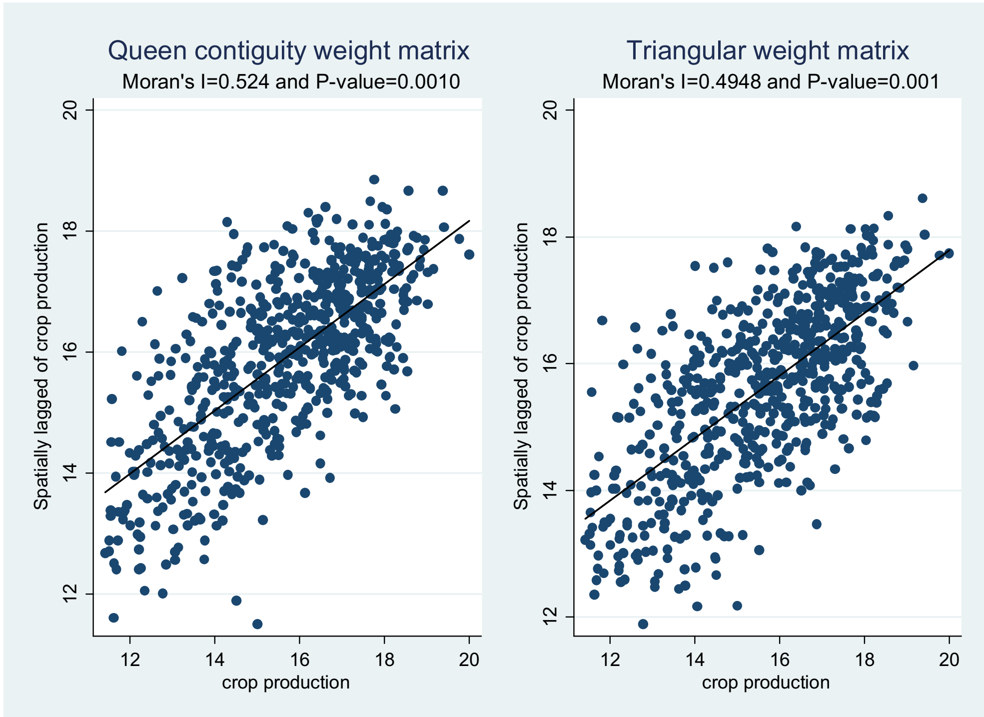

Fig. 3. Moran scatterplot for crop production (alternative weighting schemes).

triangulation matrix the centroids of each unit are created in Cartesian space and connected by a triangle node. Nodes connected by triangle edges are spatially connected. The Delaunay triangulation matrix solves the problem of outliers and ensures that every spatial unit has at least one neighbor.

We first explore whether crop production followed a random or cluster pattern in the study area based on these alternative weighting schemes. As can be seen in Fig. 3, the slope of the regression line between crop production and spatially lagged values of crop production is positive and highly significant with these two spatial weight matrices, implying a positive spatial autocorrelation. It seems that with these two spatial weight matrices, the values of Moran's I statistics are higher than those based on five-nearest neighbors (Tables 4 and 5).

The results of the GS2LS based on queen contiguity weight matrix and Delaunay triangulation matrix confirm the positive and significant effect of crop diversity on crop production. Furthermore, when rainfall is very low in the agroecosystem, crop diversity is very active in boosting crop production. Other variables are still significant and have the same interpretation. With these two alternative weighting schemes, our constructed instruments based on Lewbel (2012) still provide almost the same results.[16]

5. Conclusions and Policy Recommendations

In the current study, we use a direct market valuation approach based on a production function to examine the effect of crop diversity on major crop production in France while controlling for spatial effects. Results of the study reveal that crop diversity is positively and significantly related with major crop production and most pronounced when rainfall is low in the agroecosystem.

[16] There is evidence of endogeneity with these alternative weighting matrices and our instruments are valid.

Table 4
Spatial 2SLS estimation results (queen contiguity weight matrix).

Variables	Panel A	Panel B	Panel C	Panel D
Crop diversity	13.053***	12.944*	2.669***	2.709**
	(3.165)	(7.425)	(1.008)	(1.327)
Crop diversity × rain	−1.892***	−1.877*	−0.394***	−0.400**
	(0.445)	(1.068)	(0.141)	(0.188)
Land	−0.037	−0.036	−0.017	−0.016
	(0.032)	(0.063)	(0.025)	(0.065)
Labor	0.195***	0.194***	0.187***	0.184***
	(0.028)	(0.030)	(0.024)	(0.026)
Capital	0.226***	0.226	0.268***	0.266
	(0.031)	(0.174)	(0.026)	(0.167)
Fertilizer	0.581***	0.582***	0.531***	0.534***
	(0.031)	(0.118)	(0.026)	(0.107)
Rain	1.413***	1.399	0.277*	0.281
	(0.401)	(0.949)	(0.146)	(0.194)
Water holding capacity	0.040	0.041	0.138*	0.139
	(0.088)	(0.106)	(0.073)	(0.086)
Depth of soil	−0.014	−0.015	−0.126	−0.125
	(0.108)	(0.118)	(0.092)	(0.089)
Intercept	−5.684**	−5.594	1.658	1.622
	(2.806)	(6.457)	(1.106)	(1.579)
Spatial lag of error term	0.468***	0.542***	0.026**	0.025*
	(0.055)	(0.069)	(0.012)	(0.013)
Spatial lag of crop produc.			0.462***(a)	0.489***(a)
			(0.053)	(0.099)
N	645	645	645	645

Notes: Standard errors in parentheses. Panel A and B are the results of spatial 2SLS with homoscedasticity and heteroscedasticity with share of land with high biodiversity potential, share of farms with farm's holder under 40 years as instruments of crop diversity, respectively. Panel C and D are the results of spatial 2SLS with homoscedasticity and heteroscedasticity when we construct the internal instruments for crop diversity based on heteroscedasticity-based instruments, respectively. In all estimates, crop diversity and its interaction with rain and spatial lag of crop production are considered endogenous. *N* is the total number of observations. The spatial weight matrix used is the queen contiguity weights matrix. (a) Since the spatial lag of crop production is significant, the estimates of total effect (direct and indirect effects) due to a change in covariates are not straightforward. It is the average of all derivatives of crop production with respect to covariates. The findings are available upon request.

* $p < 0.10$.
** $p < 0.05$.
*** $p < 0.01$.

Thus, the study suggests that in the context of climate change which may result in scant rainfall, crop diversity could act as a catalyzer to crop production. Put differently, under a stress agroecosystem, our findings suggest that biodiversity could contribute to economic activity. We also find that spatial dependence exists and is mostly explained by unobserved factors or shocks which is left unattended.

The findings of the current study are robust to alternative spatial weighting schemes and suggest that spatial dependence should not be overlooked in future studies which explore the effect of crop diversity on crop production.

From a policy perspective our study suggests that in situ conservation of crop diversity should be encouraged and could be a good strategy to enhance crop production. Monetary incentives for crop rotations could provide long-term agronomic and economic benefits. In this study, we only consider the link between a specific biodiversity (crop diversity) on one crop production. A good avenue for new research could be to investigate the impact of other forms of biodiversity on crop production. It could provide insight into understanding the impact of environmental policy not devoted to crop production.

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Table 5
Spatial 2SLS estimation results (Triangular contiguity weight matrix).

Variables	Panel A	Panel B	Panel C	Panel D
Crop diversity	9.268***	9.266***	4.229***	4.216**
	(2.556)	(3.211)	(1.093)	(1.780)
Crop diversity × rain	−1.322***	−1.322***	−0.610***	−0.608**
	(0.360)	(0.453)	(0.153)	(0.249)
Land	−0.033	−0.033	−0.012	−0.012
	(0.029)	(0.066)	(0.025)	(0.060)
Labor	0.200***	0.200***	0.193***	0.194***
	(0.026)	(0.026)	(0.024)	(0.025)
Capital	0.235***	0.236	0.258***	0.259
	(0.031)	(0.169)	(0.026)	(0.161)
Fertilizer	0.568***	0.567***	0.536***	0.536***
	(0.031)	(0.108)	(0.026)	(0.100)
Rain	1.051***	1.052**	0.447***	0.445*
	(0.319)	(0.437)	(0.153)	(0.241)
Water holding capacity	0.082	0.082	0.128*	0.128
	(0.081)	(0.091)	(0.073)	(0.082)
Depth of soil	−0.074	−0.074	−0.118	−0.118
	(0.098)	(0.104)	(0.091)	(0.090)
Intercept	−3.265	−3.266	0.840	0.855
	(2.226)	(3.184)	(1.128)	(1.697)
Spatial lag of error term	0.510***	0.506***	0.473***	0.479***
	(0.046)	(0.082)	(0.044)	(0.097)
N	645	645	645	645

Notes: Standard errors in parentheses. Panel A and B are the results of spatial 2SLS with homoscedasticity and heteroscedasticity with share of land with high biodiversity potential, share of farms with farm's holder under 40 years as instruments of crop diversity, respectively. Panel C and D are the results of spatial 2SLS with homoscedasticity and heteroscedasticity when we construct the internal instruments for crop diversity based on heteroscedasticity-based instruments, respectively. In all estimates, crop diversity and its interaction with rain and spatial lag of crop production are considered endogenous. *N* is the total number of observations. The spatial weights matrix used is the triangular weight matrix.

* $p < 0.10$.
** $p < 0.05$.
*** $p < 0.01$.

Appendix A. A-spatial 2SLS estimation results

Variables	Coefficients
Crop diversity	13.240**
	(6.019)*
Crop diversity × rain	−1.844**
	(0.850)
Land	−0.157***
	(0.053)
Labor	0.247***
	(0.030)
Capital	0.428***
	(0.112)
Fertilizer	0.453***
	(0.078)
Rain	1.631**
	(0.796)
Water holding capacity	0.045
	(0.090)
Depth of soil	−0.041
	(0.106)
Intercept	−7.696
	(5.497)
N	645
Durbin-Wu-Hausman test	χ^2-value = 13.601; *p*-value = 0.000
Kleibergen-Paap LM statistic	χ^2-value = 15.990; *p*-value = 0.000
The Hansen *J* test	χ^2-value = 1.462; *p*-value = 0.481
Anderson-Rubin test	*F*-value = 1.59; *p*-value = 0.003

Notes: standard errors in parentheses. The share of land with high biodiversity potential, share of farms with farm's holder under 40 years are used as instruments of crop diversity.

* $p < 0.10$.
** $p < 0.05$.
*** $p < 0.01$.

Appendix B. Step-by-step spatial 2SLS estimation results (five-nearest neighbors)

Variables	Panel A	Panel B	Panel C	Panel D	Panel E	Panel F
Crop diversity	9.883***	13.949***	120.717***	9.905***	14.160***	121.306***
	(1.466)	(4.025)	(25.462)	(2.556)	(5.323)	(42.720)
Rain		4.485	13.171***		4.714	13.228**
		(2.796)	(3.358)		(4.424)	(6.024)
Crop diversity × rain			−16.352***			−16.433***
			(3.567)			(5.935)
Intercept	6.557***	−27.543	−83.129***	6.560**	−29.251	−83.540*
	(1.371)	(22.343)	(24.235)	(2.556)	(33.690)	(43.511)
Spatial lag of error term	0.523***	0.525***	0.643***	0.586***	0.582***	0.700***
	(0.052)	(0.055)	(0.045)	(0.058)	(0.066)	(0.062)
N	645	645	645	645	645	645

Notes: Standard errors in parentheses. Panel A, B and C are the results of spatial 2SLS with homoscedasticity with share of land with high biodiversity potential, share of farms with farm's holder under 40 years as instruments of crop diversity. Panel D, E and F are the same results with heteroscedasticity. The spatial weight matrix used is the five-nearest neighbors.

* $p < 0.10$.

** $p < 0.05$.

*** $p < 0.01$.

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