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ANALYSIS

The environmental benefits of grassroots cooperatives in agriculture

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ABSTRACT

This paper analyses the environmental benefits of grassroots cooperation in agriculture. Specifically, it focuses on the French context, which is characterised by a heavy reliance on pesticides and by strong inter-farmer interactions structured within farm machinery sharing cooperatives (CUMAs). We theorise that these social interactions are strategically complementary in the sense that the agroecological practices of farmers involved in the CUMA network, in a given spatial unit, are influenced by the presence and actions of CUMA members in their vicinity. At the extensive margin, increased peer-to-peer interactions, driven by a higher density of CUMA members, foster sociotechnical exchanges conducive to reducing pesticide use. At the intensive margin, if members individually make greater use of their CUMA, they collectively gain access to technologically advanced machinery assets, which leads to a reduction in pesticide use through improvements in technical efficiency. Our econometric analysis, based on a dataset provided by the National Federation of CUMAs covering 5793 individual cooperatives, fully supports the extensive-margin mechanism. The intensive-margin mechanism, however, is only observed for greater use of agroecological equipment by CUMA members, suggesting a rebound effect when it comes to conventional equipment. Overall, these results point to the idea of a 'hidden agroecological transition.'

1. Introduction

The reduction of pesticide use is increasingly recognised as one of the key challenges on the road to agroecology and sustainable farming systems, given its considerable environmental implications in (i) avoiding water contamination and the loss of soil biodiversity as well as (ii) in preventing illness among farmers, local communities and consumers (Wilson and Tisdell, 2001). The economics literature has so far focused on a variety of economic instruments, such as taxes, subsidies and legal regulations, to create incentives at the individual farm level and to steer farming practices towards sustainability (e.g., Finger et al., 2017; Chèze et al., 2020). However, it has largely overlooked the potentially important role of self-organised inter-farmer cooperative arrangements. Our study aims to fill this gap by examining how collective action conducted by members within grassroots cooperatives leads farmers to reduce their use of pesticides in agricultural activities.

Our study examines how institutional arrangements, neither market- nor state-mediated, but governed by peer-to-peer interactions and collective action, positively impact the environment. While a substantial body of work has demonstrated that such institutional arrangements can lead to sustainable management of natural resources (e.g., water, grassland, forestry or fishing resources) (Ostrom, 1990; Baland and Platteau, 1996; Agrawal, 2001; Persha et al., 2011), little is known on the environmental effects generated by human-made common-pool resources (Hess, 2008), chiefly cooperatives (Bauwens and Eyre, 2017; Plateau et al., 2021). Our study contributes to the academic debate by shedding light on how grassroots inter-farmer social interactions structured within grassroots cooperatives can be a catalyst for the adoption of agroecological practices.

The French context provides fertile ground for investigation. Like other Western countries, France is known to be heavily reliant on pesticides, being the world's third largest user (Jacquet et al., 2011). In fact, pesticide consumption increased by 6 % between 2011 and 2020 (Eurostat, 2022). In parallel, France provides a prime example of the vitality of self-organised, inter-farmer cooperative arrangements and innovation practices, which are adopted in the agricultural sector across both developing and developed countries. The most prevalent form of such arrangements throughout French agriculture is by far the CUMA

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(*Coopérative d'Utilisation de Matériel Agricole*) (Cornée et al., 2020). CUMAs provide a formal, legal framework enabling small groups of farmers to organise themselves into cooperatives in order to share the means of production by collectively investing in and managing machinery and other equipment assets, as well as, occasionally, labour. Currently there are more than 12,000 CUMAs involving about half of all French farmers.[1]

To establish the link between CUMA members' presence and actions in a given spatial unit and pesticide use, we draw on the literature on social networks and the key concept of strategic complementarity. As highlighted by social scientists, social interactions are ubiquitous in our lives. Most social and occupational decisions we make (e.g., buying a new product, adopting a new technology, attending a meeting, committing a crime, etc.) are influenced by others (i.e., friends, acquaintances, peers, etc.) (Granovetter, 2005; Tasselli et al., 2015; Jackson et al., 2017). In the case of agriculture, social networks have been used to understand the phenomena of peer-to-peer effects in collective action, social learning and technology adoption (Bandiera and Rasul, 2006; Conley and Udry, 2010; Baldassarri, 2015). Applied to the context of this research, the concept of strategic complementarity suggests that the actions towards agroecological practices of farmers involved in the CUMA network in a given spatial unit are influenced by the presence and actions of CUMA members in their vicinity.

Building on the research on cooperatives and, more generally, common-pool resources (e.g., Felthoven et al., 2014; Suter et al., 2019), we have derived an extensive-margin mechanism and an intensive-margin mechanism from the concept of strategic complementarity. At the extensive margin, we theorise that increased peer-to-peer interactions within the CUMA network foster the exchange of socio-technical knowledge and transfer of experience among CUMA members (and potentially other farmers in the area), promoting the adoption of environmentally friendly practices and eco-innovations by individual farmers in the CUMA's area or in neighbouring areas (i.e., spill-over effect) through the establishment of norms. At the intensive margin, we theorise that, when members individually invest more in and make greater use of their CUMA, they collectively gain access to technologically advanced machinery assets. This will, in turn, enable farmers to achieve technical efficiency gains and—provided there is no rebound effect—reduce the use of the most expensive inputs, particularly pesticides. We expect this effect to be especially strong for agroecological equipment, as it more significantly alters farmers' production function and is less susceptible to a potential rebound effect.

We test these two mechanisms using a unique, proprietary database of 5793 CUMAs obtained from the National Federation of CUMAs—this dataset represents 64 % of the 9138 CUMAs registered with the National Federation—in combination with additional data sources (notably *AGRESTE 2010*, *Agroclim* and *INSEE CLAP* databases). To assess the potential benefit on the environment, we draw on statistics from the French National Pesticide Sales Database (*BNV–d*), which compiles data from distributors of plant protection products. Our models explain the average quantity of active substances contained in plant protection products per hectare of utilised agricultural area (UAA) at the postcode level for the years 2015 and 2016—smoothing out the storage effects observed at the farm level. To isolate the effect of CUMA dynamics, we control for an array of confounding factors related to community characteristics, agricultural practices, crop types and weather conditions in the spatial units under consideration.

In a nutshell, our findings indicate that a higher presence and actions of CUMA members in a given area has significant and positive environmental effects both at the extensive and intensive margins. Greater CUMA membership density and increased use of agroecological equipment by CUMA members lead to a reduction of pesticide use. However, no significant effect is observed in terms of an increase in the use of conventional equipment, suggesting the presence of a rebound effect.

The rest of the paper is organised as follows. Section 2 presents the theoretical framework underpinning this investigation. Section 3 introduces the data and describes the empirical design. Section 4 presents the results and checks their robustness, testing various alternative specifications and accounting for model selection bias. Section 5 discusses the findings, outlines future research perspectives and draws policy implications. Section 6 concludes.

2. Theoretical framework

2.1. Agricultural cooperatives and environmental benefits

Cooperatives are economic enterprises characterised by collective property and democratic decision-making (the 'one member one vote' principle), aimed at improving their members' welfare (Hansmann, 2000). Unlike investor-owned firms, where potentially remote investors govern and make strategic decisions based on their economic power (i.e., the share of equity they hold), cooperatives are governed by collective action and social interactions between members embedded in communities (Nilsson et al., 2012).[2] Agricultural cooperatives are voluntary groups of farmers formed in order to benefit from coordinated production decisions, easier access to inputs and markets, and more effective lobbying (Di Falco et al., 2008). These cooperatives coordinate activities either vertically or horizontally (Sexton, 1986). Vertical coordination involves supply and marketing cooperatives that organise members' activities upstream and downstream of the value chain, respectively. Horizontal coordination refers to cooperatives coordinating activities among members at the same stage of the value chain.

Studies addressing the environmental impact of agricultural cooperatives have largely focused on vertical coordination. These studies consistently highlight the positive environmental effects of cooperatives, particularly for marketing cooperatives operating downstream of the value chain, which encourage members to adopt environmentally friendly practices by offering products with enhanced environmental value to local consumers (Candemir et al., 2021; Cornée et al., 2024).[3] For instance, Ma et al. (2018) find that membership in a Chinese apple-producing cooperative increases the likelihood of investing in organic soil amendments. In the same vein, Di Falco et al. (2008) find a positive relationship between the density of cooperatives and the diversity of local wheat varieties in Southern Italy. In a case study conducted on the Swiss cooperative Gran Alpin, Bardsley and Bardsley (2014) document that the high regard in which members hold this cooperative stems from its ability to market local, organic cereal products at a secure premium price, which was instrumental in promoting both local identity and environmental values.

1 Historically, the legal status of CUMAs was created in 1945, and their development has been a result either of self-help dynamics or of interventionist public policies aimed at the agricultural sector (Herbel et al., 2015). The vast majority of CUMAs belong to a regional federation to benefit from legal, accounting and technical support.

2 Unlike investor-owned firms, cooperatives are characterised by a 'bundle of rights' that strongly restricts the alienation right, which is the possibility of selling the rights to both residual control and residual earnings (Périlleux and Nyssens, 2017). Standard economic theory posits that without well-defined alienation rights ensure efficient market mechanisms, coordination among members or owners is doomed to failure, leading to organisational inefficiency (Alchian and Demsetz, 1972). The theoretical developments of Ostrom and colleagues argue strongly against this view, demonstrating that, provided the adoption of appropriate design principles, collective action can be a functional coordination mechanism to ensure organisational efficiency (Ostrom, 1990; Ostrom et al., 1992).

3 More generally speaking, some studies insist on the positive externalities generated by collective action in less formal structures of governance (e.g., Marshall, 2009; Willy and Holm-Müller, 2013).

Our study extends this literature by examining the case of the most wide-spread cooperative form of horizontal coordination vehicles, namely farm machinery cooperatives, or CUMAs (Hansmann, 1999). Farmers can access machinery resources through various ownership schemes. Privately, farmers may purchase machinery on their own—if affordable—or use the service of an agricultural contractor. CUMAs offer an alternative ownership scheme in which investment decisions and management are collectively undertaken. While a relatively modest share (around 10 %) of the total investment in farm machinery and equipment occurs collectively in CUMAs, about half of all French farmers participate as CUMA members (Herbel et al., 2015). The contribution of CUMAs—arising from networks of inter-farmer interactions—to the agroecological transition has largely gone unnoticed due to the implicit nature of these practices. Yet, recent sociological research suggests that CUMA members make use of the intensified interpersonal relationships established through machinery sharing arrangements to foster mutual aid, facilitate the transfer of experience and, more broadly, enable social learning processes that may ultimately lead to the realisation of agroecological innovations and investments (Lucas et al., 2019). While farmers generally prefer to work with peers whose profiles resemble their own, pioneer farmers are open to collaborating with those of different profiles to explore sociotechnical complementarities and steepen the learning curve (Lucas and Gasselin, 2023). In what follows, to establish potential causal mechanisms (Heckman, 2008), we theorise that the social interactions among CUMA members act as a potent institutional facilitator for a transition to agroecology.

2.2. Strategic complementarity at the extensive and intensive margins

2.2.1. Strategic complementarity

As defined in the theory of social networks, strategic complementarity between players in a game suggests that "*[…] a player's incentives to take an action (or a 'higher' action) are increasing in the number of his or her friends who take the (higher) action […]*" (Jackson and Zenou, 2015, p. 98). In our case, this general proposition helps us distinguish between two channels that explain why a farmer's use of pesticides is influenced by the presence and actions of CUMA members in his/her vicinity. At the extensive margin, we contend that the more peers a farmer interacts with in a structured network (i.e., in a CUMA), the more he/she would be encouraged to change his/her behaviour towards lower pesticide use. At the intensive margin, we contend that the higher the level of activity within the network (i.e., greater use of CUMA assets) by a farmer's peers, the more the farmer is incentivised to reduce his/her pesticide use. We now elaborate on these mechanisms—established at the individual level—and derive testable hypotheses at an aggregated level, that of spatial units.

2.2.2. Extensive margin

Why should farmers reduce their pesticide use more if they are in a spatial unit with a higher number or proportion of CUMA members? We argue that CUMAs enable strategies to reduce pesticide use through improved interpersonal relationships between members resulting from the design and implementation of machinery-sharing arrangements. The starting point of our argument is that farmers with heterogeneous pesticide reduction strategies coexist, whether or not they belong to a CUMA. A logic of economic optimisation, a logic of innovation and an environmental logic based on health considerations can typically be identified (Chantre and Cardona, 2014). Regardless of the underlying logic, farmers tend not to make radical changes, but rather they adopt new practices gradually. Technological and economic uncertainties may explain the reluctance to reduce pesticide use (Bjørnåvold et al., 2022). Moreover, the drivers of pesticide reduction appear to depend less on individual farmer characteristics and more on structural and relational factors at the local level; with grassroots collective action among farmers as a key driver, where certain farmers set an example for others (Young et al., 2022). Being a member of a CUMA may foster a mimetic effect whereby observing and imitating peers encourages farmers to reduce their misuse or overuse of pesticides (Liu and Wu, 2022). CUMAs likely increase members' 'perceived behavioural control' not only by demonstrating alternatives but also by empowering farmers to gain more control over their own production and by promoting more planned pesticide applications (Bakker et al., 2021; Meunier et al., 2024). Likewise, the individual planning resulting from collective action in CUMAs can eliminate inefficiencies and reduce pesticide use (Kahindo and Blancard, 2022). Taken together, these factors strongly suggest that, far from being trivial, the by-product of peer-to-peer interactions in CUMAs enable members to enhance their sociotechnical capacities and increase their willingness to adopt ecological innovations (De Marchi, 2012).

The mechanisms described above, which occur at the CUMA level among heterogeneous members, can be replicated at the local level between CUMA farmers and non-CUMA farmers. CUMAs can be seen as laboratories, from which non-CUMA farmers in the same area may eventually benefit. This echoes the role often attributed to cooperatives and social and solidarity economy enterprises as a yardstick for transformative change (Novkovic, 2022; Rousselière et al., 2024). In addition, there are potential spill-over effects whereby the peer-to-peer dynamics observed in CUMAs in one area can influence (non-) CUMA farmers in neighbouring areas (Luo et al., 2017). Overall, this suggests that a peer-to-peer effect, associated with the density of CUMA members should be detectable at both the local and extra-local levels. Because of observational equivalence, this effect could result from interactions occurring within and/or outside CUMAs in their operating areas and in neighbouring areas. This brings us to our first hypothesis:

H1. Extensive-margin mechanism: The higher the number or proportion of CUMA members within farmers in a given area, the greater the reduction of pesticide use in this area and in neighbouring areas.

2.2.3. Intensive margin

Why should farmers reduce their pesticide use more if they are in a spatial unit where CUMA members use their CUMA more intensively? Strategic complementarity suggests that the intensity with which a farmer invests in and uses CUMA machinery varies as a function of the average level of use and investment made by other CUMA members. This is consistent with both cooperative and common-pool resource theories, which posit that stronger economic commitment to the group limits members' exit options, reduces discount rates, and conversely increases members' exposure to the collective action effects generated by the group (Ostrom et al., 1994; Fulton and Giannakas, 2001; Ostrom, 2010). Commitment is particularly binding in CUMAs, where members contractually agree to a pre-defined number of machine hours when investing. If members fail to meet the required number of hours, they may be obliged to compensate the CUMA.[4] This means that if the number of hours for a financially viable investment is not reached, the investment may not go ahead. If however, on average, members increase their usage of the CUMA—whether simultaneously or sequentially—, they can afford technologically advanced machinery that would otherwise be out of reach with less intensive use. Access to upgraded technology should enable farmers to improve their technical efficiency and reduce their reliance on pesticides, which are deemed to be among the costliest inputs of the production function (Paul et al., 2019). This proposition holds, under the assumption that there is no rebound effect (Song et al., 2018). Technological progress can not only enhance pesticide efficiency but, paradoxically, it can also boost the economic potential of farms, alter farmers' behaviour and ultimately raise the demand for pesticides, thereby partially or fully offsetting any savings resulting from efficiency gains (Brunelle et al., 2024).

As shown by Cornée et al. (2020), machinery assets in CUMAs can be

[4] For this reason, the equivalence between the use of machinery assets and investment is almost perfect.

characterised by both a quantitative and qualitative dimension. The quantitative aspect relates to the volume of machinery available per member in a CUMA, while the qualitative aspect refers to the types of machinery available. Machinery assets vary in their environmental and community impact. Some machinery is considered 'agroecological equipment' because it promotes soil health and fertility and reduces pesticide use (Lucas et al., 2019). The terms of the quantity-quality agreements, which is not necessarily a trade-off, vary between CUMAs. Members may value differently the consequences of their investment choices—which involve assets that cannot be transferred outside the CUMA's area of operation—not only for their occupational practices but also for the community and sustainability (Askildsen et al., 2006; Sacchetti, 2015). Furthermore, the nature of the relationship between CUMAs and the community varies from area to area. Certain CUMAs, by virtue of their embeddedness in the community in which they operate, are more subject to local pressure—whether mediated by members or not—and therefore more inclined to adopt environmentally friendly strategies (Carchano et al., 2024).

We expect the impact of access to advanced technology through increased CUMA participation to be magnified when we focus specifically on the adoption of agroecological equipment, for three reasons. First, such equipment is often more expensive than conventional equipment (Harris and Fulton, 2000; Wolfley et al., 2011). Second, it may result in more profound changes to the production function than conventional machinery, leading to a sharper decline in pesticide use. Third, agroecological equipment can often serve as a complete substitute for pesticides (e.g., mechanical weed control)—whereas conventional equipment merely offers a more efficient use of pesticides (e.g., precision farming/decision support systems)—, thereby limiting the possibility of a rebound effect. This brings us to our second hypothesis:

H2. Intensive-margin mechanism: The fact that members in a given spatial unit make more intensive use of their CUMA's machinery assets, particularly agroecological equipment, leads to a greater reduction in pesticide use.

3. Data and methods

3.1. Data

Table 1 defines and describes the sources of the variables used in the empirical analysis, and Table 2 presents the summary statistics for these variables. Our data are retrieved from five main sources. First, the data on pesticide consumption for the years 2015 and 2016 are drawn from the French National Pesticide Sales Database (*Banque nationale des ventes des distributeurs, BNV–d* database). The 2006 law on water and the aquatic environment requires authorised distributors of plant protection products to declare their annual sales within the national territory. These data on pesticide consumption are then used to calculate the quantity of active substances, based on a repository that indicates the composition of each product.[5] As our baseline model, we use the total quantity of active substances purchased in the buyer's postcode area per hectare of UAA (*Substances per UAA hectare*). Only 8 % of all postcode areas—mostly urban—report zero pesticide sales. Moreover, there is considerable heterogeneity across areas, as shown in Fig. 1.

Second, we use a unique, proprietary dataset obtained from the National Federation of CUMAs, which provides detailed information, at the individual CUMA level, including financial statements (balance sheets and income statements), members, equipment and machinery assets. We have access to 5793 CUMAs, representing 64 % of all French CUMAs.[6] As described in Table 1, the variables *# CUMA members* and *% CUMA members* indicate the number of CUMA members and the proportion of farmers belonging to a CUMA in a spatial unit (i.e., postcode area), respectively. We assume that all members of a CUMA are located within the postcode area of their CUMA. In reality, a tiny minority of members may reside in a neighbouring postcode area different to that of their CUMA. Using the residence of CUMA members instead of the location of CUMAs does not affect the results. The variable *# Equipment per member* represents the average volume of equipment (expressed in

Table 1
Definition of variables.

Variable	Definition
Dependent variable	**BNV–d database**
Substances per UAA hectare	Active substances contained in plant protection products purchased by all buyers in the postcode area / Postcode area's utilised agricultural area (UAA) hectares
Independent variables	
CUMA variables	**CUMA proprietary database**
# CUMA members	Total number of farmers that are members of a CUMA in the postcode area
% CUMA members	Number of CUMAs members / Number of farmers in the postcode area, in %
# Equipment per member	Average number of equipment items per member per CUMA at the postcode level
% Agroecological equipment	Average number of agroecological equipment items out of total number of equipment items used by members per CUMA at the postcode level, in %
# Members per CUMA	Average number of members per CUMA at the postcode level
Total assets per CUMA	Average total net asset value per CUMA at the postcode level
Community-related variables	***INSEE CLAP* and *Assemblée Permanente des Chambres d'Agriculture***
Social economy	Social and solidarity economy establishments / Total number of public and private sector establishments in 2015 at the postcode level, in %
Agricultural election turnout	Election turnout to the chambers of agriculture for each *département* in 2013, in %
FNSEA voters	FNSEA (*Fédération nationale des syndicats d'exploitants agricoles*) voters in the Chambers of Agriculture in 2013 at the *département* level, in %
Agroeconomic variables	***AGRESTE 2010* database, averaged at the postcode level**
UAA	Utilised agricultural area (UAA) in hectares (arable land, permanent grassland, and permanent crops) / Total area in hectares, in %
# Farms	Number of farms
Farm potential production	Average gross potential agricultural production per farm, in € 1000
Cereals	Cereal surfaces UAA/ Total UAA, in %
Vineyards	Vineyard surfaces UAA/ Total UAA, in %
Market gardening/horticulture	Market gardening and horticulture surfaces UAA/ Total UAA, in %
Orchards	Orchard surfaces UAA/ Total UAA, in %
Grassland	Grassland surfaces UAA / Total UAA, in %
Organic/labels	Hectares in organic and traceability labels (i.e., Protected Designation of Origin, Protected Geographical Indication and Red Labels) / Total UAA (excluding wine-growing productions), in %
Weather variables	***US Agroclim* Database at the postcode level**
Winter/ Spring/ Summer/ Autumn precipitation	Total seasonal precipitation, in millimetres
Winter/ Spring/ Summer/ Autumn temperature	Average seasonal temperature, in Celsius degrees

[5] The total quantity of active substances includes, in particular, the most environmental harmful substances labelled as 'toxic, very toxic, carcinogenic or mutagenic substances'.

[6] To reduce the effect of possibly spurious outliers, we performed a winsorisation transformation at the 99th percentile for variables *# CUMA members* and *# Equipment per member*. For these variables, all values above the 99th percentile were set to the 99th percentile.

Table 2
Descriptive statistics.

Variables	Obs.	Mean	Std. Dev.	Min	Max
Dependent variable					
Substances per UAA hectare					
Total	9296	7.35	35.97	0	1689.67
Toxic, very toxic, carcinogenic or mutagenic	9296	1.55	9.07	0	581.83
Independent variables					
CUMA variables					
# CUMA members	9296	46.27	91.60	0	502
% CUMA members	9296	38.29	37.10	0	100
# Equipment per member	9296	0. 77	1.18	0	5.8
% Agroecological equipment	9296	14.62	18.50	0	100
# Members per CUMA	9296	16.48	27.39	0	148.4
Total assets per CUMA	9296	129,083.4	232,764.2	0	6,178,700
Community-related variables					
Social economy	9296	9.54	4.35	0	40.42
Agricultural election turnout	9296	53.81	6.82	40.49	75.23
FNSEA voters	9296	58.34	10.45	28.88	81.08
Agroeconomic variables					
UAA	9296	48.87	27.67	0.05	451.29
# Farms	9296	82.43	92.53	0	1324
Farm potential production	9296	103.68	78.52	0.2	1374.62
Cereals	9296	19.10	26.72	0	100
Vineyards	9296	4.92	16.53	0	100
Market gardening/horticulture	9296	0.78	5.24	0	99.16
Orchards	9296	0.99	5.30	0	76.60
Grassland	9296	29.72	28.50	0	100
Organic/labels	9296	0.06	0.16	0	3.69
Weather variables					
Winter precipitation	9296	158.61	178.61	6.28	1948.97
Spring precipitation	9296	150.94	178.30	6.92	1961.76
Summer precipitation	9296	109.23	126.00	1.15	1191.58
Autumn precipitation	9296	138.86	152.22	4.22	1323.84
Winter temperature	9296	5.24	2.23	−6.75	10.81
Spring temperature	9296	10.06	1.79	−3.07	15.05
Summer temperature	9296	19.11	2.07	7.33	24.93
Autumn temperature	9296	11.50	1.74	0.77	17.69

Note: The variables # *CUMA members* and # *Equipment per member* are winsorised at the 99th percentile.

number of items) owned per member per CUMA at the postcode level. The variable *% Agroecological equipment* represents the average share of agroecological equipment in the total machinery used by members per CUMA at the postcode level. Based on a classification provided by the National Federation of CUMAs, we can calculate the proportion of equipment owned and used by CUMA members that promotes agroecological practices, including directly reducing the use of phytosanitary products, improving soil fertility, promoting farm autonomy (e.g., in terms of protein, fodder or seeds) and developing local marketing channels.[7] The average size of a CUMA is captured by two variables *# Members per CUMA* and *Total assets per CUMA*, which represent the average number of members per CUMA and the average value of total assets per CUMA (expressed in natural logarithm) at the postcode level. Examining these variables allows us to characterise CUMA member activity. 45 % of all spatial units contain at least one CUMA. There are on average 46.27 CUMA members per postcode area, though the number varies widely across postcode areas, with a standard deviation of 91.60. CUMAs are a highly popular method for sharing machinery; indeed, 38.29 % of farmers are CUMA members. On average, a CUMA member uses 0.77 pieces of equipment, of which 14.62 % are considered as agroecological. The average size of a CUMA is 16.48 members, with total assets averaging €129,083.

Third, we use three variables to capture the local (agricultural) community context in which CUMAs operate, both culturally and politically. The variable *Social economy* indicates whether CUMA dynamics can be found in areas characterised by a vibrant fabric of community-led initiatives. It is defined as the number of social economy (short for social and solidarity economy) establishments divided by the total number of public and private establishments (9.72 %) and is computed using data retrieved from the *CLAP* survey conducted by *INSEE* (*Institut national de la statistique et des études économiques*) in 2015. Social economy includes cooperatives, non-profits and mutuals, which are collective organisations owned and controlled by their members. As democratic organisations rooted in communities, they play a key role in fostering local initiatives that address social needs and aspirations that are neither met by the state nor the market (Punt et al., 2022; Ziegler et al., 2023; Rousselière et al., 2024). Additionally, the variables *Agricultural election turnout* and *FNSEA voters* aim to capture the type of farmers' unionism and agricultural system preferred in a given CUMA area. These variables are based on data from the French Permanent Assembly of the Chambers of Agriculture (*Assemblée permanente des chambres d'agriculture*) for the year 2013. A high election turnout with a significant vote in favour of the main farmers' union, FNSEA (*Fédération nationale des syndicats d'exploitants agricoles*), could indicate an area in which the mainstream agricultural system dominates and in which there is less diversity in terms of farmers' unionism (Cordellier, 2008; Salhorgne, 2008). On average, 58.34 % of farmers vote for FNSEA in agricultural elections.

Fourth, we include a set of agroeconomic control variables that align with the state of the art in agricultural economics. These control variables are sourced from the *AGRESTE 2010* database, which corresponds to the data collected by the French Ministry of Agriculture's statistical service during the 2010 agricultural census. The percentage of UAA in

[7] This classification was created by the National Federation of CUMAs (FNCUMA) at the request of the French Ministry of Agriculture, in the context of Law No. 2014–1170 of 13 October 2014 on the future of agriculture, with the aim of facilitating the practical implementation of agroecology in order to achieve economic, environmental and social performance on French farms.

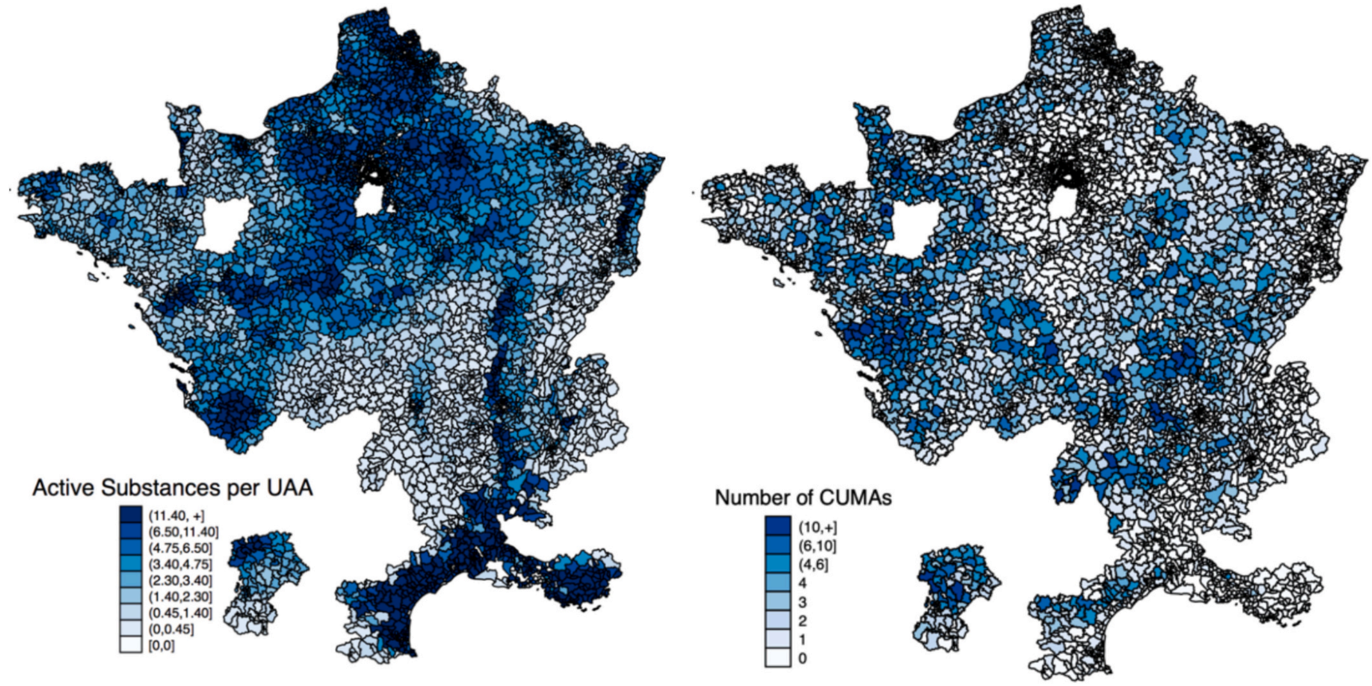

Fig. 1. Active substances per UAA hectare and number of CUMAs per postcode area, 2015–2016.

total area (*UAA*),[8] the number of farms (*# Farms*) and the potential agricultural production per farm in thousands of euros (*Farm potential production*)[9] serve as indicators for the level of agriculture activity in each postcode area. On average, the UAA represents 48.87 % of the total postcode area, and there are 82.43 farms per postcode area. In addition to these farm characteristics, the existing literature also indicates that the use of pesticides is influenced by the type of landscape and land cover characteristics in a given area (Skevas et al., 2013; Larsen et al., 2015; Larsen and Noack, 2017; Zhang et al., 2018; Larsen and McComb, 2021). Areas characterised by high landscape diversity typically exhibit lower pesticide demand compared to more homogeneous areas, which are often more susceptible to pests and natural enemies. The *AGRESTE 2010* database provides two indicators for identifying the type of landscape and land cover characterising each hectare of UAA. First, the hectares of UAA are classified by production type, i.e., their type of technical-economic orientation, which includes cereal field crops, vineyards, market gardening and horticulture, orchards, or livestock. More specifically, a given farm's UAA is considered to be specialised if one type of production exceeds two thirds of its total production (calculated in terms of standard gross production). If a type of production accounts for less than two thirds of its total production, the farm's UAA is classified as unspecified/diversified. The second indicator is the proportion of UAA hectares covered by permanent grassland. Therefore, in order to characterise the type of landscape and land cover for one hectare of UAA, we include these two indicators in our empirical analysis. The technical-economic orientations (i.e., *Cereals, Vineyards*, *Market gardening/horticulture* and *Orchards*) reflect the percentage of UAA in each postcode area dedicated to cereal field crops (19.10 %), vineyards (4.92 %), market gardening/horticulture (0.78 %) and orchards (0.99 %). Livestock production is excluded due to a high correlation with the variable *Grassland* (correlation coefficient of 0.75).[10] On average, grassland represents 29.72 % of the UAA. Finally, the agroeconomic control variables also include the variable *Organic/labels*, which corresponds to the share of the UAA dedicated to organic or traceability-labelled crops (i.e., protected designation of origin, protected geographical indication and Red Label production). Production quality schemes of this type, which are expected to reduce pesticide use (Chèze et al., 2020), represent on average 0.06 % of the UAA at the postcode level.

Fifth, the weather control variables are drawn from the *US Agroclim* database provided by INRAE (*Institut national de recherche pour l'agriculture, l'alimentation et l'environnement*). Studies examining the economic impact of climate change on crop farming (especially in Europe) using a Ricardian approach mainly use two types of indicators: growing season degree-days, on the one hand, and total precipitation or four-season average temperature and precipitation variables (often modelled with non-linear and quadratic relationships), on the other hand. Four-season models are more accurate when it comes to controlling for climate effects outside the growing season (Massetti et al., 2016). To avoid correlation issues, recent studies emphasise the importance of seasonal climate data, especially on a European continental scale, due to the importance of winter crops (Van Passel et al., 2017; Moretti et al., 2021). Indicators focused solely on the growing season may underestimate the importance of cold temperatures in winter—which are relevant to European agriculture (Vaitkeviciute et al., 2019). In addition to direct effects on productivity, climate conditions also indirectly affect pesticide use, in that the climate influences insect and crop pest population dynamics (Deutsch et al., 2018;

[8] The utilised agricultural area abbreviated as UAA, is a standardised concept in European agricultural statistics. UAA is the total area, expressed in hectares, taken up by arable land (temporary pastures, fallow land, greenhouse crops, family gardens, etc.), permanent grassland and permanent crops (vineyards, orchards, etc.) used by the holding, regardless of the type of tenure or of whether it is used as a part of common land.

[9] This represents more precisely the potential value of production per hectare (in €) for each farm at production prices and yields without financial aid.

[10] This means that the average per postcode area of the sum of the technical-economic orientations retained for our analysis (expressed as a percentage of the total UAA at the postcode level) is 25.79 %. The difference between this percentage and 100 % corresponds to the technical-economic orientation 'livestock' (19.79 %) and to an unspecified/diversified technical-economic orientation. Note that our analysis yields almost similar findings when we also include 'livestock'. However, we prefer not to do so in order to avoid any multicollinearity problem.

Lehmann et al., 2020). For example, cold temperatures reduce pest incidence in Europe. Therefore, we include seasonal temperature and precipitation data at the postcode level.

3.2. Regression models

In order to identify the specific influence of CUMAs on the overall use of pesticides in a given area, we estimate two panel data regression model specifications, which are straightforward extensions of the standard weather approach to pesticide demand.

3.2.1. Extensive-margin model

To test hypothesis H1, we use the model displayed in Eq. (1), which examines how the density of CUMA members (vector C^{EM}) as well as agroeconomic covariates (vector A) and weather covariates (vector W) influence pesticide use over the 2015–2016 period for the 4653 postcode spatial units of France. This postcode random-effects model, which is estimated with robust standard errors clustered at the postcode level to control for heteroscedasticity and temporal autocorrelation, is specified as follows:

$$Q_{it} = cst + \gamma' {C^{EM}}_{it} + \beta' A_i + \theta' W_{it} + \alpha_i + \varepsilon_{it} \tag{1}$$

Q represents the total yearly quantity of active substances in natural logarithm, per hectare of UAA (*Substances per UAA hectare*). Vector C^{EM} includes two variables used to approximate the density of CUMA members at the spatial unit level: the number of CUMA members (*# CUMA members*) and the proportion of farmers involved in a CUMA (*% CUMA members*). Vector C^{EM} also includes two variables that control for CUMA size: *# Member per CUMA* and *Total assets per CUMA*. Vector A includes the above-mentioned list of agroeconomic controls. Agricultural activity is captured by the variables *UAA*, *# Farms* and *Farm potential production*, while the landscape and land use characteristics of a spatial unit are measured by the variables accounting for technical-economic orientations (i.e., *Cereals, Vineyards*, *Orchards* and *Market gardening/horticulture*), the variable *Grassland* and the variable *Organic/labels*. All these ratios are expressed in terms of hectares of UAA at the postcode level. Vector W controls for seasonal temperatures and precipitations at the postcode level.

To address potential endogeneity between the presence of CUMA members and other community-related factors, we use a 'plug-in' method, which, under certain conditions, falls under the broader category of control function approaches (Wooldridge, 2015). The two-stage residual inclusion (2SRI) method developed by Terza et al. (2008) is a semi-parametric approach that is more efficient than other methods, such as the two-stage least square (2SLS) method, because it better accommodates the specific nature (binary, count, ordinal, etc.) of the endogenous explanatory variable (Wooldridge, 2015: 429). In the first stage, we estimate the number or proportion of CUMA members by using the agroeconomic controls from Eq. (1) and the variables intended to account for the community-related factors (i.e., *Social economy*, *Agricultural election turnout* and *FNSEA voters*). In the second stage, we add the generalised residuals of the first stage to the baseline model as displayed in Eq. (1) to obtain a consistent estimate of the effect of CUMA members at the extensive margin, with bootstrap-corrected standard errors. As stated by Wooldridge (2015), the parameters from plug-in methods applied to cross-section data can be interpreted as average causal effects.

To account for potential externalities arising from peer-to-peer cooperation, i.e., the possibility that CUMA members in one spatial unit influence those in neighbouring units, we run alternative specifications of Eq. (1) in which vector C^{EM} also includes either the number of CUMA members or their proportion (expressed as a percentage of farmers) in neighbouring postcode areas. The adjacency matrix used to define the neighbourhood corresponds to the spatially lagged variables of *# CUMA members* and *% CUMA members* in neighbouring postcode areas.

3.2.2. Intensive-margin model

To hypothesis H2, we use the model displayed in Eq. (2), which gauges how the intensity of use of a CUMA's (agroecological) equipment by its members affects pesticide use. This model is estimated with the following equation:

$$Q_{it} = cst + \gamma' {C^{IM}}_{it} + \beta' A_i + \theta' W_{it} + \alpha_i + \varepsilon_{it} \tag{2}$$

In the specification shown in Eq. (2), the dependent variable as well as the agroeconomic and weather covariates in vectors A and W remain unchanged from Eq. (1). However, vector C^{IM} includes proxies used to capture the intensive-margin mechanism, i.e., *# Equipment per member* and *% Agroecological equipment*. Vector C^{IM} also controls for CUMA size: *# Member per CUMA* and *Total assets per CUMA*. To account for potential endogeneity issues and to adequately isolate the impact of more or less intensive use of a CUMA (agroecological) equipment by its members from other community-related effects, we use the same two-stage control function methodology as employed for the extensive-margin model. In the first stage, we estimate *# Equipment per member* and *% Agroecological equipment*, using the agroeconomic and community-related factors. In the second stage, we inject the generalised residuals from the first stage into the model specified in Eq. (2).

4. Results

4.1. Strategic complementarity at the extensive margin

4.1.1. Baseline model

Our hypothesis H1 anticipates that a higher density of CUMA members within an area will lead to closer, peer-to-peer sociotechnical interactions, which in turn will promote the adoption of ecological practices. Table 3 presents various specifications of Eq. (1) and aims to gauge this impact produced by inter-farmer interactions while controlling for an array of confounding agroeconomic and weather factors and endogeneity issues. Column (1) examines the effect of strategic complementarity at the extensive margin by analysing the number of CUMA members at the postcode level. The negative coefficient on *# CUMA members* is markedly significant both statistically (at the 1 % level) and economically. In line with our econometric causality strategy (Heckman, 2008), the results indicate that the presence of one additional CUMA member in a given postcode area decreases pesticide use by about 0.07 %.[11] Column (2) also examines the peer-to-peer density at the territorial level by including the proportion of CUMA members among farmers at the postcode level. The negative coefficient (also significant at the 1 % level) on *% CUMA members* indicates that a 1 % increase in the proportion of CUMA members in a given postcode area decreases pesticide use by about 0.08 %.

Regarding the control variables, the CUMA-related covariates are uninformative, as none of them are consistently significant. The agroeconomic covariates indicate that the quantity of pesticides used is logically dependent on the level of agricultural activity, as measured by *UAA*, *# Farms* and *Farm potential production*. The type of production also has the expected effect: pesticide use is driven upwards by *Cereals*, *Vineyards* and *Orchards*, and downwards by *Grassland*. Quality and traceability based farming approaches (proxied by *Organic/labels*) are associated with a decrease in pesticide use. The weather covariates have the anticipated coefficients in terms of both sign and significance.

4.1.2. Control function

The estimates in columns (3) and (4) in Table 3 correspond to the

[11] This actually corresponds to the elasticity provided by the estimated coefficient for a continuous variable in a regression with a log-transformed dependent variable using natural logarithm (Van Garderen and Shah, 2002).

Table 3
Strategic complementarity at the extensive margin.

	Dependent variable: Substances per UAA ha (log)					
	Baseline		Control Function		Contiguity Matrix	
	(1)	(2)	(3)	(4)	(5)	(6)
CUMA variables						
# CUMA members	−0.0007***	.	−0.0008***	.	−0.0005***	.
	(0.0001)		(0.0001)		(0.0001)	
% CUMA members		−0.0008**		−0.0009***		0.0010
	.	(0.0423)	.	(0.0001)	.	(0.0007)
# Members per CUMA	−0.0009	−0.0021*	−0.0011	−0.0020	−0.0004	−0.0019
	(0.0011)	(0.0012)	(0.0013)	(0.0014)	(0.0011)	(0.0012)
# Members per CUMA^2	1.4e-5**	1.3e-5	1.6e-5	1.3e-5	1.1e-5	1.2e-5
	(9.9e-06)	(1e-05)	(1.3e-05)	(1.3e-05)	(9.7e-06)	(9.9e-06)
Total assets per CUMA (ln)	−0.0005	0.0014	4.3e-6	0.0016	0.0002	0.0016
	(0.0022)	(0.0023)	(0.0024)	(0.0024)	(0.0022)	(0.0023)
Residuals: # CUMA members			−0.0006**			
			(0.0003)			
Residuals: % CUMA members				1.428		
				(1.049)		
# CUMA members in neighbouring postcode areas					−0.0007***	
					(0.0001)	
% CUMA members in neighbouring postcode areas						−0.0031***
						(0.0007)
Agroeconomic variables						
UAA	0.0029***	0.0029***	0.0029***	0.0029***	0.0032***	0.0031***
	(0.0006)	(0.0006)	(0.0003)	(0.0003)	(0.0006)	(0.0006)
# Farms	0.0004***	0.0002*	0.0004***	0.0002***	0.0005***	0.0002**
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Farm potential production	0.0008***	0.0008***	0.0008***	0.0008***	0.0008***	0.0007***
	(0.0002)	(0.0002)	(0.0001)	(0.0001)	(0.0002)	(0.0002)
Cereals	0.0076***	0.0076***	0.0075***	0.0076***	0.0074***	0.0075***
	(0.0005)	(0.0005)	(0.0002)	(0.0002)	(0.0005)	(0.0005)
Vineyards	0.0271***	0.0273***	0.0271***	0.0272***	0.0269***	0.0268***
	(0.0008)	(0.0008)	(0.0005)	(0.0005)	(0.0008)	(0.0008)
Market gardening/horticulture	0.0266***	0.0265***	0.0266***	0.0265***	0.0265***	0.0265***
	(0.0047)	(0.0047)	(0.0022)	(0.0022)	(0.0047)	(0.0048)
Orchards	0.0352***	0.0352***	0.0352***	0.0352***	0.0347***	0.0341***
	(0.0026)	(0.0026)	(0.0012)	(0.0012)	(0.0026)	(0.0026)
Grassland	−0.0079***	−0.0078***	−0.0079***	−0.0078***	−0.0077***	−0.0074***
	(0.0006)	(0.0007)	(0.0003)	(0.0003)	(0.0006)	(0.0006)
Organic/labels	−0.0035***	−0.0034***	−0.0034***	−0.0034***	−0.0033***	−0.0032***
	(0.0007)	(0.0007)	(0.0003)	(0.0003)	(0.0007)	(0.0007)
Weather variables						
Winter precipitation	0.00004	0.00004	0.00004	0.00004	0.00004	0.00003
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Spring precipitation	0.0001***	0.0002***	0.0001***	0.0001***	0.0001***	0.0001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Summer precipitation	−0.0001	−0.0001	−0.0001	−0.0001	−0.0001	−0.0001
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Autumn precipitation	0.0002***	0.0002***	0.0002***	0.0002***	0.0002***	0.0002***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Winter temperature	0.0279***	0.0283***	0.0281***	0.0283***	0.0285***	0.0292***
	(0.0041)	(0.0041)	(0.0042)	(0.0042)	(0.0041)	(0.0041)
Spring temperature	0.0813***	0.0819***	0.0815***	0.0818***	0.0837***	0.0847***
	(0.0098)	(0.0098)	(0.0109)	(0.0110)	(0.0098)	(0.0098)
Summer temperature	−0.0301***	−0.0303***	−0.0302***	−0.0302***	−0.0314***	−0.0314***
	(0.0068)	(0.0068)	(0.0080)	(0.0080)	(0.0068)	(0.0068)
Autumn temperature	−0.0283***	−0.0287***	−0.0282***	−0.0286***	−0.0274***	−0.0282***
	(0.0092)	(0.0092)	(0.0104)	(0.0104)	(0.0092)	(0.0092)
Random effects	Postcode	Postcode	Postcode	Postcode	Postcode	Postcode
# Observations	9296	9296	9296	9296	9296	9296
# Clusters	4648	4648	4648	4648	4648	4648
AIC	10,354.7	10,370.9	10,354.4	10,372.3	10,338.7	10,336.3

Notes: Random-effects estimations. Regression coefficients and clustered standard errors are in parentheses. Intercepts are not reported. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Columns (3) and (4) display bootstrapped clustered standard errors.

application of the 2SRI method. The first-stage regressions are presented in columns (1) and (2) in Table A1 in Appendix A. These regressions—a Poisson random-effects model in column (1) and a Tobit model in column (2)—reveal the factors driving the territorial presence of CUMA members (either in absolute or relative value). This plausibly allows us to better understand the community dynamics of the areas where CUMA members are located and captures farmers' motivations at the aggregated postcode level. As expected, areas with more active social economy initiatives (*Social economy*) show a higher presence of CUMA members. Conversely, CUMA members are less prevalent in areas with a stronger attachment to the mainstream agricultural system, as indicated by higher election turnout and a greater percentage of votes in favour of the dominant farmers' union (i.e., FNSEA). By design, the variable *FNSEA voters* also reflects the diversity of farmers' axiological views. The negative coefficient on *FNSEA voters* confirms that CUMA members flourish in areas with pluralistic views on agriculture (Salhorgne, 2008).

Most agroeconomic variables also have intuitive coefficients. For example, CUMA membership is understandably more prevalent in areas with a higher proportion of UAA and a greater number of farms, as indicated by the positive coefficients on the variables *UAA* and *# Farms*. CUMA membership also tends to thrive in areas characterised by quality-oriented farming practices *(Organic/ labels)*. The results of the second stage regressions, which include the residuals of the first-stage regression, are displayed in columns (3) and (4) in Table 3. The results hold, and the effects of both *# CUMA members* and *% CUMA members* are even stronger, thereby indicating that the baseline results presented in columns (1) and (2) are conservative estimates.

4.1.3. Contiguity matrix

Columns (5) and (6) offer an alternative strategy for capturing the mechanism of complementarity strategy at the extensive margin, i.e., by examining the impact of CUMA member density in neighbouring postcode areas on pesticide use in a given area. The negative coefficients (significant at the 1 % level) on *# CUMA members in neighbouring postcode areas* and *% CUMA members in neighbouring postcode areas* provide additional evidence of the influential effect produced by peer-to-peer interactions. This suggests that inter-farmer cooperation structured by CUMAs not only promotes pesticide reduction within a given area, but also extends its influence towards neighbouring areas.

4.2. Strategic complementarity at the intensive margin

4.2.1. Baseline model

Our hypothesis H2 anticipates that, within a spatial unit, more intensive use of a CUMA's machinery assets by its members, particularly agroecological equipment, will drive a greater reduction in pesticide use. In Table 4, we put this hypothesis to the test by estimating Eq. (2). The effect of strategic complementarity at the intensive margin is captured the variables *# Equipment per member* and *% Agroecological equipment*. The agroeconomic and weather factors controlled for are similar to those included in Table 3. The nonsignificant coefficient on *# Equipment per member* in column (1) in Table 4 indicates that more intensive use of a CUMA's total equipment by its members has no impact on the use of pesticides, potentially highlighting a rebound effect. In unreported alternative specifications,[12] we found that these nonsignificant results persist when the amount of equipment per member is measured in monetary value rather than volume. By contrast, the negative coefficient (significant at the 5 %) on *% Agroecological equipment* in column (2) reveals that the effect of strategic complementarity at the intensive margin only operates for agroecological equipment. At the intensive margin, the qualitative aspects of the collectively owned machinery used by CUMA members, have a more decisive influence than the quantitative aspects. Regarding the control variables, as shown in Table 4, the CUMA-related, agroeconomic and weather covariates behave almost similarly to those displayed in Table 3 and thus have the expected signs.

4.2.2. Control function

The estimates in columns (3) and (4) in Table 4 corresponds to the application of the 2SRI method. The first-stage regressions, displayed in columns (3) and (4) in Table A1 in Appendix A, use Poisson random-effects models to decipher the community-related and agroeconomic determinants driving the intensity of CUMA equipment use. Generally speaking, the same variables influence both categories of equipment (i.e., total and agroecological). *Social economy* has a positive impact, while *FNSEA voters* has a negative impact, further reinforcing the idea that community-related variables are good predictors of CUMA dynamics at both the intensive and extensive margins, and the explanations given in Section 4.1 remain valid here. Most agroeconomic variables also have

Table 4
Strategic complementarity at the intensive margin.

	Dependent variable: Substances per UAA ha (log)			
	Baseline		Control Function	
	(1)	(2)	(3)	(4)
CUMA variables				
# Equipment per member	0.0031	0.0054	−0.0039	0.0051
	(0.0047)	(0.0047)	(0.0057)	(0.0056)
% Agroecological equipment	.	−0.0025**	.	−0.0025***
		(0.0006)		(0.0002)
# Members per CUMA	−0.0027**	−0.0021*	−0.0028**	−0.0021
	(0.0012)	(0.0012)	(0.0015)	(0.0015)
# Members per CUMA^2	1.6e-05	1.2e-05	1.6e-05	1.2e-05
	(9.9e-06)	(9.9e-06)	(1.2e-05)	(1.3e-05)
Total assets per CUMA (ln)	−0.0005	0.0031	0.0005	0.0032
	(0.0023)	(0.0025)	(0.0028)	(0.0029)
Residuals: # Equipment per member	.	.	−0.0132	−0.0056
			(0.0101)	(0.0257)
Residuals: % Agroecological equipment	.	.	.	0.0178
				(0.0678)
Agroeconomic variables				
UAA	0.0028***	0.0029***	0.0029***	0.0029***
	(0.0006)	(0.0006)	(0.0003)	(0.0003)
# Farms	0.0002*	0.0002*	0.0002***	0.0002***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Farm potential production	0.0008***	0.0008***	0.0008***	0.0008***
	(0.0002)	(0.0002)	(0.0001)	(0.0001)
Cereals	0.0077***	0.0077***	0.0077***	0.0076***
	(0.0005)	(0.0005)	(0.0002)	(0.0002)
Vineyards	0.0275***	0.0272***	0.0275***	0.0272***
	(0.0008)	(0.0008)	(0.0004)	(0.0004)
Market gardening/ horticulture	0.0267***	0.0267***	0.0267***	0.0267***
	(0.0047)	(0.0047)	(0.0017)	(0.0017)
Orchards	0.0357***	0.0356***	0.0357***	0.0356***
	(0.0026)	(0.0026)	(0.0013)	(0.0013)
Grassland	−0.0078***	−0.0078***	−0.0078***	−0.0077***
	(0.0006)	(0.0007)	(0.0003)	(0.0003)
Organic/labels	−0.0035***	−0.0035***	−0.0035***	−0.0035***
	(0.0007)	(0.0007)	(0.0003)	(0.0003)
Weather variables				
Winter precipitation	0.00004	0.00004	0.00004	0.00004
	(0.000)	(0.000)	(0.000)	(0.000)
Spring precipitation	0.0001***	0.0001***	0.0001***	0.0001***
	(0.000)	(0.000)	(0.000)	(0.000)
Summer precipitation	−0.0001	−0.0001	−0.0001	−0.0001
	(0.000)	(0.000)	(0.000)	(0.000)
Autumn precipitation	0.0002***	0.0002***	0.0002***	0.0002***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Winter temperature	0.0279***	0.0281***	0.0279***	0.0281***
	(0.0041)	(0.0041)	(0.0042)	(0.0042)
Spring temperature	0.0813***	0.0815***	0.0813***	0.0815***
	(0.0098)	(0.0098)	(0.0111)	(0.0112)
Summer temperature	−0.0302***	−0.0304***	−0.0304***	−0.0304***
	(0.0068)	(0.0068)	(0.0082)	(0.0082)
Autumn temperature	−0.0292***	−0.0296***	−0.0292***	−0.0296***
	(0.0092)	(0.0092)	(0.0109)	(0.0101)

(*continued on next page*)

[12] The results are available upon request to the authors.

Table 4 (*continued*)

	Dependent variable: Substances per UAA ha (log)			
	Baseline		Control Function	
	(1)	(2)	(3)	(4)
Random effect	Postcode areas	Postcode areas	Postcode areas	Postcode areas
# Observations	9302	9302	9302	9302
# Clusters	4653	4653	4653	4653
AIC	10,376.8	10,369.2	10,378.1	10,373.1

Notes: Random-effects estimations. Regression coefficients and clustered standard errors are in parentheses. Intercepts are not reported. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Columns (3) and (4) display bootstrapped clustered standard errors.

meaningful coefficients. For example, the positive and significant effect of *Farm potential production* suggests that members make a greater use of CUMA equipment in areas where agriculture is sufficiently developed and has defined mechanisation needs. Areas specialised in specific types of production (*Cereals*, *Vineyards*, *Market gardening/horticulture* and *Orchards*) are less conducive to CUMA utilisation, whereas more diversified farming systems (*Grassland*) increase the intensity of equipment use. Interestingly, *Organic/labels* has a positive and significant impact on *% Agroecological equipment* but no effect on *# Equipment per member*. The generalised residuals obtained from the first-stage regressions are included in the baseline models as displayed in columns (3) and (4) in Table 4. The results hold, and the effect of % *Agroecological equipment* is even stronger, thereby confirming that our baseline results presented in columns (1) and (2) are conservative estimates.

4.3. Robustness analyses

4.3.1. Alternative specifications

Here we present the results of alternative specifications that check the robustness of our main findings. First, we use an alternative proxy for the dependent variable. For the baseline estimations, we use the total quantity of active substances. In Table B1 in Appendix B, we replicate the analysis using a different dependent variable but the same regressors. Specifically, we replace the total quantity of active substances (*Substances per UAA hectare*) with a subcategory of the most environmentally harmful substances, such as those classified as toxic, very toxic, carcinogenic or mutagenic. Overall, the estimations displayed in Table B1 in Appendix B, are consistent with the baseline results.

Second, we ensure that the positive effect of CUMA dynamics on reducing the use of pesticides is not determined by the type of production carried out in each spatial unit. In Table B2 in Appendix B, we interact the proxies for strategic complementarity mechanisms at the extensive and intensive margins with the variables capturing farms' technical-economic orientations. The results show no variation in the CUMA effect based on production type, except for areas with market gardening and horticulture, where the CUMA effect is less pronounced or non-existent. This is consistent with the inelastic demand for pesticides in 'speciality crops' where fewer substitutes exist such as gardening and horticulture (Böcker and Finger, 2017).

Third, we run additional estimations to assess the sensitivity of our main results to changes in samples. The dependent variable used in our baseline regressions (i.e., the total quantity of active substances) is characterised by a high level of dispersion as shown by its standard deviation in Table 2. To ensure that our results are not driven by extreme observations, we exclude postcode spatial units with a zero value for the variable *Substances per UAA hectare* and remove the last percentile of this variable's distribution to exclude its highest values. The results shown in Table B3 in Appendix B, are similar to those from the baseline regressions.

Finally, we check the consistency of our findings using a different model specification. In Table B4 in Appendix B, we include additional random effects, namely for the *Petites Régions Agricoles* (PRAs), defined by the Ministry of Agriculture as small areas characterised by agroecological homogeneity according to various factors including landscape diversity (Mouysset et al., 2013). Our results remain robust to this change in specification.

4.3.2. Model averaging and multi-model inference

Because we test the two effects of strategic complementarity sequentially, our results may be subject to omitted variable bias, data dredging, model uncertainty, and, more generally, model selection bias (Chatfield, 1995). Significant extensive-margin effects may simply be artefacts due to not simultaneously controlling for intensive-margin effects, and vice versa. Model uncertainty arises when one theory does not rule out the other. These various problems can lead to biased statistical inferences and over-optimistic standard errors, since the results do not take into account the complete set of possible models that could have been explored (Steel, 2020). To address these various problems, we develop a frequentist model averaging approach, also known as multi-model inference (Burnham and Anderson, 2004). This approach has already been used to identify the best candidate models for assessing wildlife-friendly gardening practices (Goddard et al., 2013). As shown by Burnham and Anderson (2004), this approach, when based on an information criterion such as the Akaike information criterion (AIC), allows for the estimation of multiple models and has properties similar to Bayesian model averaging (Steel, 2020).

Using all the variables introduced in our main analysis leads to the estimation of 72 different models. In order to limit the model space (i.e., the number of possible combinations of variables), we systematically include agroeconomic and weather control variables in all potential models. We also control for local specialisation in agriculture using PRAs. Parameters are averaged over all models using the AIC weights, which indicate the probability that a model is the best among the candidate set. Standard errors also account for uncertainty in the model selection process. To implement this procedure, we use the MuMin package for R developed by Barton (2023).

The main results of this procedure are reported in Table B5 in Appendix B. Columns (1) and (2) present the full models including all proxy variables for both extensive- and intensive margin effects, without and with the PRA random-effects, respectively. Columns (3) and (4) present the averaged parameters and standard errors with and without controlling for PRA random effects, respectively. Overall, Table B5 indicates that our main results remain valid. In particular, the model averaging specifications displayed in columns (3) and (4) provide strong evidence

Table 5
Hypotheses: test and corroboration.

Hypothesis	Test	Corroboration
H1. Extensive-margin mechanism: The higher the number or proportion of CUMA members within farmers in a given area, the greater the reduction of pesticide use in this area and in neighbouring areas.	In Table 3: Negative and significant coefficients on the variables *# CUMA members* and *% CUMA members*.	**Yes** (including control function, contiguity matrix, alternative estimations and simultaneous testing of H1 and H2)
H2. Intensive-margin mechanism: The fact that members in a given spatial unit make more intensive use of their CUMA's machinery assets, particularly agroecological equipment, leads to a greater reduction in pesticide use.	In Table 4: Nonsignificant coefficient on the variable *# Equipment per member*. Negative and significant coefficient on the variable *% Agroecological equipment*.	**Yes** (including control function, alternative estimations and simultaneous testing of H1 and H2)

that further supports the robustness of our baseline results, as the coefficients on our main variables of interest (i.e., *# CUMA members*, *% CUMA members*, *# Equipment per member*, *% Agroecological equipment*) have a consistently significant and negative impact on pesticide demand.

5. Discussion

5.1. Main findings

Table 5 summarises the extent to which empirical analysis supports hypotheses H1 and H2. Hypothesis H1 is fully supported, highlighting a mechanism of strategic complementarity at the extensive margin. A stronger presence of CUMA members, or a higher proportion of CUMA members among farmers in a given spatial unit, leads to increased sociotechnical peer interactions and the implementation of norms, based on processes of imitation and behavioural control, through which farmers are influenced and incentivised to reduce pesticide use. Interestingly, this peer-to-peer effect also goes beyond the boundaries of the CUMAs' areas of operation, spilling over to (non-CUMA) farmers in neighbouring areas.

Regarding hypothesis H2, more intensive use of CUMAs by their members does not produce any significant negative effect on pesticide use per se. In other words, the technical efficiency gains at the farmer level made possible by an increased volume of shared total equipment, are not observed, suggesting that they are offset by a potential rebound effect. In contrast, the proportion of agroecological equipment used by the members of a CUMA has a negative effect on pesticide use, suggesting that technical efficiency gains and improvements in the production function are not plagued by a rebound effect. In short, it is only for the use of agroecological equipment by CUMA members that a mechanism of strategic complementarity can be detected at the intensive margin.

Our findings are robust to the inclusion of an array of variables that account for confounding effects, to the application of a control function approach, to changes in model specifications, and the treatment of model selection bias (i.e., model averaging). The two mechanisms of strategic complementarity are confirmed whether estimated separately or together in a complete model. Our baseline models show that the presence of each additional CUMA member in a postcode area leads to a reduction in pesticide use of 0.07 %. Moving from a postcode area with zero CUMA members to one with an average of 104 CUMA members, the average in areas where there is at least one CUMA, results in a reduction of 7.28 %. The effect is also noteworthy for agroecological equipment: a 1 % increase in its proportion leads to a 0.25 % decrease in pesticide use. In general, the elasticities in the reduction in pesticide use related to the presence of CUMAs are homogeneous across all types of production. The exception is market gardening and horticulture (with a significantly lower elasticity), due to the lack of substitutes for pesticide use (Böcker and Finger, 2017).

5.2. Research perspectives

First, while the extensive-margin mechanism indicates that peer-to-peer interactions occur among CUMA farmers, our results may also reflect a yardstick effect, whereby CUMA members influence non-CUMA farmers. This warrants further investigation. For instance, a higher density of CUMA members in a given area may exert additional pressure on non-CUMA farmers, encouraging them to adopt similar behavioural norms. This aligns with studies showing that farmers' willingness to cooperate in community-based management of natural pest control or conservation practices depends on the (perceived) proportion of potential cooperators in the area (Marshall, 2009; Stallman and James Jr, 2015). In the same vein, our findings indicate that the reduction in pesticide use through peer-to-peer CUMA-based interactions is not confined to the CUMAs' areas but spill over into neighbouring areas. Further investigation is needed to understand this phenomenon fully. In particular, this spill-over effect may not only stem from grassroots 'peer-to-peer' relationships but may also be driven by the federative network of CUMAs. Cooperative federations are deemed to play a decisive role in the transfer of experience and knowledge between local cooperative organisations (Ingram and Simons, 2002).

Second, we cannot rule out the possibility that the intensive-margin mechanism, associated with the type of equipment a CUMA can afford based on its members' participation, is sensitive to local pesticide demand. Such an analysis, based on quantile regressions to detect heterogeneous spatial effects of CUMAs, could be conducted with greater confidence if more comprehensive data were available on the presence of CUMAs nationwide. In particular, we do not have data for the South-West of France, which accounts for a large proportion of the national wine production, and which is a major consumer of pesticides. In this region, CUMA members may behave differently if they collectively own more expensive, heavier specialised equipment.

Third, the first-stage regressions used in the control function approach provide information on the drivers of the CUMA dynamics at the intensive and extensive margins. The presence and actions of CUMA members flourish in areas characterised by pluralistic views on agriculture, a weaker attachment to the mainstream agricultural system, diversified farming systems, and developed production quality schemes. CUMA dynamics are also strongly correlated with community-related factors, such as the development of other types of social economy organisations. Further empirical studies are needed to better understand why farmers become members of a CUMA and their level of participation in that CUMA.

Fourth, CUMAs are generally regarded as one of the last remaining arenas where farmers with different farm sizes, farming systems and axiological viewpoints coexist and interact (Piet et al., 2012; Bokusheva and Kimura, 2016; Lucas and Gasselin, 2023). This achievement may be related to members refraining from explicitly communicating the environmental benefits of their innovations, thereby preventing ideological conflict from disrupting sociotechnical exchanges, conducted under the guise of shared goals, such as enhancing autonomy at the farm level. This seems especially true in CUMAs where member profiles are highly diverse, giving rise to a norm of 'tacit silence' on the most divisive of environmental issues ('keep your ideas in the locker room') (Lucas et al., 2019). Fieldwork (e.g., farmer interviews) would be valuable in delving into these interactions among CUMA members, which are often motivated by distinct axiological systems. Indeed, the amount and forms of communication within CUMAs can influence both the nature and economic outcomes of strategic complementarity among members at the extensive margin (e.g., the quality of peer-to-peer effects) and at the intensive margin (e.g., coordination in investment choices).

Fifth, our regressions systematically control for the size of CUMAs (i.e., number of members) and also include the quadratic term to capture potential non-linear effects. Although the coefficients on these variables cannot really be interpreted due to their weak and unstable statistical power, it can be observed that CUMAs are, on average, characterised by a small number of members. Small size is a key condition for fruitful dialogue and interaction between farmers (Nilsson et al., 2012). The question of how CUMAs deliberately (or not) restrict their size to favour participation and democracy, while coordinating at upper levels in a federative network should be investigated further (Cornée et al., 2020).

5.3. Policy implications

Our study sheds new light on effectively reducing the level of pesticide use in agriculture by unearthing the case of grassroots inter-farmer cooperation as a game changer. This question has rarely been considered in the economics literature and in policy measures. Public policies include prohibitive measures by banning or severely restricting the use of certain active substances, as the EU has done (Aka, 2017). Alternatively, differentiated taxation schemes can create leverage and effects on pesticide use and therefore increase the acceptability of pesticide taxes through redistributive measures (Finger et al., 2017). At the micro level, various approaches examine the decision-making process of individual farmers when they need to change their pesticide use behaviour. Increasingly widespread experimental studies (e.g., discrete choice experiments) seek to determine the weight of each decision-making factor, as well as to estimate farmers' willingness to pay for/ willingness to accept changes in these factors. Sufficiently high payments are typically required by farmers as a production-risk premium (i. e., compensation for the increased risk of large production losses) and an administrative burden premium (Chèze et al., 2020). Our research study complements these approaches and highlights the importance of collective action in removing obstacles to the adoption of environmentally friendly practices by farmers.

6. Conclusion

This paper's main contribution lies in highlighting the environmental benefits of grassroots cooperation in agriculture. Our study focuses on the French context, which is characterised by both major environmental challenges due to its high reliance on pesticides, and a dense web of inter-farmer local interactions, and more specifically through farm machinery sharing cooperatives (CUMAs). Theoretically, we argue that these social interactions are strategically complementary in the sense that that the agroecological practices of a farmer involved in the CUMA network in a given spatial unit are influenced by the presence and actions of CUMA members in his/her vicinity. At the extensive margin, this implies that more peer-to-peer interactions driven by a higher density of CUMA members foster sociotechnical exchanges conducive to reducing pesticide use. At the intensive margin, this implies that if members individually make greater use of their CUMA, they collectively have access to technologically up-to-date machinery, thereby reducing pesticide use through technical efficiency gains. Our empirical analysis entirely confirms the extensive-margin mechanism, even highlighting a spill-over effect whereby peer-to-peer interactions between CUMA members in a spatial unit influence farmers in neighbouring areas. At the intensive margin, increased utilisation of a CUMA's agroecological equipment by its members leads to a reduction in pesticide use. However, there is no significant result in terms of an increase in the use of conventional equipment, suggesting that technical efficiency gains are cancelled out by a rebound effect. Taken together, our findings support the idea of a 'hidden agroecological transition' enhanced by CUMAs (Lucas et al., 2019). While this transition may be viewed as incremental, the CUMA effect is still remarkable. In particular, sociotechnical exchanges between peers at local level encourage farmers to reflect on their practices and therefore offer them a promising way to shift away from the dominant sociotechnical regime, which is considered to be hindering to the development of agroecological innovations (Vanloqueren and Baret, 2009).

Our study echoes previous work conceptualising CUMAs as human-made common-pool resources (Cornée et al., 2020). While the extensive-margin mechanism may refer to the way farmers appropriate the resource flow (i.e., the way farmers use the CUMA machinery assets), the intensive-margin mechanism may correspond to qualitative changes made to the resource stock (i.e., collective investment in agroecological machinery assets). More generally, our work contributes to the debate on the plurality of (grassroots) cooperatives' objectives (Gui, 1991; Fulton and Giannakas, 2013). Cooperatives should be regarded as organisations that seek not only to promote the mutual interest of their members (i.e., maximising members' economic welfare), but also the well-being of the community (Peredo and Chrisman, 2006; Defourny and Nyssens, 2010; Plateau et al., 2021).

CRediT authorship contribution statement

Simon Cornée: Writing – review & editing, Writing – original draft, Validation, Resources, Project administration, Methodology, Investigation, Conceptualization. **Damien Rousselière:** Writing – review & editing, Validation, Software, Resources, Project administration, Methodology, Investigation, Formal analysis, Conceptualization. **Véronique Thelen:** Writing – review & editing, Visualization, Validation, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The authors do not have permission to share data.

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Appendix A. Two stage residual inclusion (2SRI) method

Table A1
First-stage estimation of the number of CUMAs.

Dependent variable	# CUMA members	% CUMA members	# Equipment per member	% Agroecological equipment
	(1)	(2)	(3)	(4)
Community-related variables				
Social economy	0.090***	1.099***	0.019***	0.325***
	(0.010)	(0.124)	(0.006)	(0.057)
Agricultural election turnout	−0.016**	−0.265***	−0.003	−0.077**
	(0.007)	(0.077)	(0.003)	(0.038)
FNSEA voters	−0.050***	−0.816***	−0.021***	−0.258***

(*continued on next page*)

Table A1 (*continued*)

Dependent variable	# CUMA members	% CUMA members	# Equipment per member	% Agroecological equipment
	(1)	(2)	(3)	(4)
	(0.005)	(0.050)	(0.002)	(0.025)
Agroeconomic variables				
UAA	0.025***	0.316***	0.021***	0.171***
	(0.003)	(0.023)	(0.002)	(0.017)
# Farms	0.011***	0.043***	0.004***	0.056***
	(0.001)	(0.007)	(0.001)	(0.006)
Farm potential production	0.001	−0.025***	0.002***	0.007**
	(0.001)	(0.007)	(0.001)	(0.003)
Cereals	0.002	−0.196***	−0.005***	−0.081***
	(0.004)	(0.021)	(0.001)	(0.009)
Vineyards	−0.003	−0.329***	−0.004*	−0.185***
	(0.003)	(0.058)	(0.002)	(0.013)
Market gardening/horticulture	−0.031***	−0.349***	−0.022**	−0.074***
	(0.010)	(0.029)	(0.001)	(0.023)
Orchards	−0.021*	−0.711***	−0.028***	−0.208***
	(0.011)	(0.092)	(0.009)	(0.032)
Grassland	0.012***	0.019	0.006***	0.049***
	(0.003)	(0.023)	(0.001)	(0.009)
Organic/labels	0.006***	0.220***	0.0001	0.036**
	(0.002)	(0.033)	(0.001)	(0.016)
Random effects	Postcode areas	Postcode areas	Postcode areas	Postcode areas
# Observations	9296	9296	9296	9296
# Clusters	4648	4648	4648	4648
AIC	48,228.2	90,854.6	17,872.2	77,536.3

Notes: (1), (3) and (4) are Poisson random-effects estimation. (2) is a Tobit estimation. Regression coefficients and clustered standard errors are in parentheses. Intercepts are not reported. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Appendix B. Robustness checks

Table B1
Alternative dependent variable: most environmentally harmful substances.

Dependent variable: Toxic, very toxic, carcinogenic or mutagenic substances per UAA hectare (log)				
	(1)	(2)	(3)	(4)
CUMA variables				
# CUMA members	−0.0006***	.	.	.
	(0.001)			
% CUMA members	.	−0.0007**	.	.
		(0.0003)		
# Equipment per member	.	.	−0.0023	−0.00004
			(0.0041)	(0.0040)
% Agroecological equipment	.	.	.	−0.0020***
				(0.0004)
Other CUMA variables	Yes	Yes	Yes	Yes
Agroeconomic variables	Yes	Yes	Yes	Yes
Weather variables	Yes	Yes	Yes	Yes
Random effects	Postcode areas	Postcode areas	Postcode areas	Postcode areas
# Observations	9296	9296	9296	9296
# Clusters	4648	4648	4648	4648
AIC	4293.7	4483.6	4322.9	4310.6

Notes: Random-effects estimations. Clustered standard errors are in parentheses. Intercepts are not reported. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table B2
Interaction terms: interacting with types of production.

	Dependent variable: Substances per UAA hectare (log)			
	(1)	(2)	(3)	(4)
CUMA variables				
# CUMA members	−0.0008***	.	.	.
	(0.0001)			
% CUMA members	.	−0.0011**	.	.
		(0.0005)		
# Equipment per member	.	.	−0.0030	0.0057
			(0.0064)	(0.0047)
% Agroecological equipment	.	.	.	−0.0032***
				(0.0007)
Agroeconomic variables				

(*continued on next page*)

Table B2 (*continued*)

	Dependent variable: Substances per UAA hectare (log)			
	(1)	(2)	(3)	(4)
Cereals	0.0075***	0.0074***	0.0076***	0.0074***
	(0.0005)	(0.0006)	(0.0005)	(0.0005)
Vineyards	0.0269***	0.0269***	0.0275***	0.0269***
	(0.0009)	(0.0009)	(0.0009)	(0.0009)
Market gardening/horticulture	0.0249***	0.0249***	0.0249***	0.0251***
	(0.0048)	(0.0048)	(0.0048)	(0.0049)
Orchards	0.0370***	0.0376***	0.0353***	0.0363***
	(0.0024)	(0.0026)	(0.0026)	(0.0024)
Interaction effects with	**# CUMA members**	**% CUMA members**	**# Equipment per member**	**% Agroecological equipment**
X Cereals	1.4e-6	4.9e-6	0.0002	1.9e-5
	(0.000)	(0.000)	(0.0002)	(0.0000)
X Vineyards	8.1e-6	1.7e-5	−4.4e-5	5.7e-5
	(0.000)	(0.000)	(0.0003)	(0.000)
X Market gardening/horticulture	0.0003***	0.0009***	0.0115**	0.0007**
	(0.0001)	(0.0002)	(0.0046)	(0.0003)
X Orchards	0.0001**	−0.0002	0.0015	-0.0002
	(0.0001)	(0.0001)	(0.0019)	(0.0003)
Other CUMA variables	Yes	Yes	Yes	Yes
Other agroeconomic variables	Yes	Yes	Yes	Yes
Weather variables	Yes	Yes	Yes	Yes
Random effects	Postcode areas	Postcode areas	Postcode areas	Postcode areas
# Observations	9296	9296	9296	9306
# Clusters	4648	4648	4648	4653
AIC	10,340.6	10,299.5	10,373.9	10,365.9

Notes: Random-effects estimations. Clustered standard errors are in parentheses. Intercepts are not reported. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table B3
Alternative sample: removing atypical individuals in terms of pesticide use.

	Dependent variable: Substances per UAA hectare (log)			
	(1)	(2)	(3)	(4)
CUMA variables				
# CUMA members	−0.0007***	.	.	.
	(0.0001)			
% CUMA members	.	−0.0026***	.	.
		(0.0003)		
# Equipment per member	.	.	- 0.0051	−0.0003
			(0.0056)	(0.0055)
% Agroecological equipment	.	.	.	−0.0042***
				(0.0006)
Other CUMA variables	Yes	Yes	Yes	Yes
Agroeconomic variables	Yes	Yes	Yes	Yes
Weather variables	Yes	Yes	Yes	Yes
Random effects	Postcode areas	Postcode areas	Postcode areas	Postcode areas
# Observations	8444	8444	8444	8444
# Clusters	4222	4222	4222	4222
AIC	7181.4	7132.5	7215.1	7173.0

Notes: Random-effects estimations. Clustered standard errors are in parentheses. Intercepts are not reported. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The postcode spatial units reporting a zero value for the variable *Substances per UAA* as well as the last percentile of this variable are removed from the sample.

Table B4
Alternative model specification: using postcodes and PRAs random effects.

		Dependent variable: Substances per UAA hectare (log)		
	(1)	(2)	(3)	(4)
CUMA variables				
# CUMA members	−0.0007***	–	–	–
	(0.0001)			
% CUMA members	–	−0.0008**	–	–
		(0.0003)		
# Equipment per member	–	–	0.0030	0.0054
			(0.0089)	(0.0089)
% Agroecological equipment	–	–	–	−0.0025***
				(0.0008)
Other CUMA variables	Yes	Yes	Yes	Yes
Agroeconomic variables	Yes	Yes	Yes	Yes
Weather variables	Yes	Yes	Yes	Yes
Random effects				
Postcode areas	Yes	Yes	Yes	Yes

(*continued on next page*)

Table B4 (*continued*)

	Dependent variable: Substances per UAA hectare (log)			
	(1)	(2)	(3)	(4)
PRAs	Yes	Yes	Yes	Yes
# Observations	9296	9296	9296	9296
# Clusters	4648	4648	4648	4648
AIC	10,356.7	10,372.9	10,378.8	10,371.2

Notes: Random-effects estimations. Clustered standard errors are in parentheses. Intercepts are not reported. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table B5
Alternative modelling approach: using frequentist model averaging.

	Dependent variable: Substances per UAA ha (log)			
	Complete models		Model averaging	
	(1)	(2)	(3)	(4)
CUMA variables				
# CUMA members	−0.0007***	−0.0007***	−0.0006***	−0.0006***
	(0.0002)	(0.0002)	(0.0001)	(0.0001)
% CUMA members	−0.0003	−0.0002	−0.0009**	−0.0008*
	(0.0004)	(0.0004)	(0.0004)	(0.0004)
# Equipment per member	−0.0019	−0.0019	−0.0060	−0.0025
	(0.0091)	(0.0091)	(0.0075)	(0.0074)
% Agroecological equipment	−0.0023***	−0.0022***	−0.0024***	−0.0022***
	(0.0008)	(0.0008)	(0.0009)	(0.0008)
# Members per CUMA	−0.0004	−0.0007	0.0004	0.0006
	(0.0013)	(0.0012)	(0.0006)	(0.0006)
# Members per CUMA^2	0.0000	0.0000	0.0000**	0.0000**
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Total asset per CUMA (ln)	0.0039	0.0054*	−0.0015	−0.0003
	(0.0033)	(0.0033)	(0.0021)	(0.0021)
Agroeconomic variables	Yes	Yes	Yes	Yes
Weather variables	Yes	Yes	Yes	Yes
Random Effects				
Postcode areas	Yes	Yes	Yes	Yes
PRAs	No	Yes	No	Yes
# Observations	9296	9296	9302	9302
AIC	10,684.7	10,542.2		

Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are in parentheses. Intercepts are not reported.

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