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Farm economic resilience, land diversity and environmental uncertainty

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Abstract:

Economic resilience is a concept used for farms facing shocks and their capacity to resist, adapt and achieve new equilibria enhancing their long term viability. Operationalizing the resilience concept is a difficult task due to its multidimensional and dynamic nature. Based on literature and risk management theory, this paper develops a composite index of economic resilience based on five dimensions, namely farm's vulnerability, intensification, biodiversity, diversification and performance. In a second step, the composite index is used to estimate the impact of climatic, environmental and telecommunications infrastructure factors on the economic resilience of farms in England and Wales, using multilevel models with mixed effects estimators. Results show that CAP subsidies, soil erosion and drought have a negative impact on the economic resilience of English and Welsh farms, but that a more diversified land use reduces farms' vulnerability, by providing more opportunities for agricultural diversification. Finally, extensive telecommunications infrastructure has a particularly important role in the economic resilience of the pigs sector.

Acknowledegment:

JEL Codes: Q18, O13

#443

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***Key words*:** economic resilience, risk management, multilevel mixed-effects, subsidies

***JEL* classification:** O13, Q12, Q18, Q54

1. Introduction

The agricultural sector is facing a series of challenges, both at local and global level, which can potentially reduce its long-term viability and sustainability. Such challenges are production and market risks (e.g. pests, weather risks and volatile markets), policy uncertainty (e.g. Brexit), changes in climate and environmental conditions (e.g. climate change and soil erosion), and unfair trade practices (UTPs) in the agri-food supply chain (Fałkowski et al., 2017). These challenges can create challenging and more competitive conditions under which farmers need to operate to obtain sufficient returns to make a living. In many countries, especially among the European Member States, the agricultural sector is under a significant structural change, with a large number of agricultural holdings exiting the sector, lower occupation and with few farmers under the age of 35 continuing the activity of their farming families (Schuh et al., 2016).

To address these negative conditions and structural change, and to improve the long-term sustainability of the agricultural sector in the EU, policymakers are increasing support to agricultural risk management and sustainable practices (e.g. greening). Moreover, improving the resilience of the agricultural sector, making it more resistant to risks and uncertainties, more adaptable to changes, and more capable to achieve new equilibriums aftershocks, is now an important policy goal. The underlying reason for policymakers to support farms' resilience, is that viable and sustainable farming systems are important for ensuring food security and the health of rural economies and communities.

Resilience is a concept that has recently moved from socio-ecological research circles to become a policy framework for agriculture (Darnhofer, 2014). Several studies have attempted to operationalize resilience in different contexts, such as food security (Alinovi et al., 2010), rural and local economies (Béné, 2013), ecosystems (Cabell and Oelofse, 2013) and cities (ARUP, 2014). However, operationalizing resilience for agricultural economics purposes still remains a challenging task because of the multi-dimensional nature of resilience (Cabell and Oelofse, 2013), and because resilience is a context-specific concept, in which dimensions change depending on the location.

A large part of the current resilience literature approached the issue from either a conceptual (e.g. Darnhofer, 2014; Tendall et al., 2015) or a qualitative point of view (e.g. Darnhofer, 2010; Doeksen and Symes, 2015; Darnhofer et al., 2016). Several attempts to estimate farms' resilience have also been attempted. In many of these studies, farming resilience has been framed in relation to agrobiodiversity and agroecosystems, measuring resilience mainly as a function of crop diversity (Di Falco and Chavas, 2006; Di Falco and Chavas, 2008; Quaas and Baumgartner, 2008; Di Falco et al., 2010; Matsushita et al., 2016; Chavas and Di Falco, 2017). Other studies used farm diversification strategies (Peerlings et al., 2014), input use intensity (Hamerlinck et al., 2014) and farms' performance (Abson et al., 2013) to measure resilience.

Although we recognize the validity of these studies and their importance in contributing to the operationalization of economic resilience of farms, the main drawback common to all of them is the use of a single measure (farms' agrobiodiversity, diversification, intensification or performance) to quantify and estimate resilience. As such, these approaches are limited in that they fail to address the multi-dimensional nature of resilience.

The aim of this paper is to present the preliminary results of an ongoing piece of research that builds on existing literature, to develop an analytical framework for measuring resilience based on the identification of its components in an agricultural and economic context. The resilience of a given farm depends on physical (e.g. assets; income-generating activities; agrobiodiversity) and capacity dimensions (e.g. adaptive capacity and vulnerability to risks). Because resilience is not observable but it is a function of its components, the measurement of resilience is based on selecting proxy variables for each identified dimension of resilience

(Alinovi et al., 2010). An aggregate measure of the economic resilience of farms is therefore developed in the form of a composite indicator, called ERI (Economic Resilience Index), calculated for farms in England and Wales, UK. The main data source is farm accountancy data (Farm Business Survey – UK) and, given that resilience is also dynamic, the ERI is developed for a time series of ten years.

In addition to developing a resilience index, this paper also provides an econometric application of the ERI, by estimating the impact of exogenous factors on the economic resilience of farms in England and Wales. These exogenous factors relate to climate, environment and telecommunications infrastructure. The exogenous factors are obtained using a combination of land cover data and other geospatial datasets. The nature of the data is such that the exogenous factors are calculated at regional (county) level. Therefore, the econometric approach relies on multilevel-hierarchical models with mixed effects estimators.

Results show that the CAP subsidies have a negative impact on the economic resilience of English and Welsh farms, especially for the cereals, horticulture, poultry and dairy sectors. A more diversified land use reduces a farms' vulnerability, by providing more opportunities for agricultural diversification, especially for the most land-intensive sectors such as grazing livestock and cereals. Among environmental factors, soil health is a key driver of farms' economic resilience, as soil erosion drastically reduces resilience. The same applies to drought risks. Finally, extensive telecommunications infrastructure, in the form of broadband in rural areas, has a particularly important role in the economic resilience of the pigs sector, reducing the producers' remoteness to market and increasing the possibilities of reacting promptly and effectively to changes in the supply chain.

The remainder of the paper is structured as follows. Section 2 explains how the ERI has been calculated and describes the spatial relationships that exist between the resilience dimensions.

Section 3 develops the econometric application of ERI, explaining the econometric strategy and the results. Conclusions are offered in Section 4.

2. Measuring farms' economic resilience

Farms' economic resilience is a multidimensional concept that describes the capacity of the farm system to maintain its current economic viability in face of perturbations, such as market and production risks and policy change, and eventually to shift into a new state of equilibrium.

Our approach to farms' economic resilience builds on the framework RIMA (Resilience Index Measurement and Analysis model) successfully used by the FAO to measure household resilience to food insecurity (Alinovi et al. 2008; 2010). As resilience is not directly observable, Alinovi et al. (2008; 2010) model resilience as a function of multiple household characteristics, in the form of physical and capacity dimensions.

Moreover, our approach builds also on risk theory, which explains that, at the farm level, a risk-averse farmer shifts part of his resources from production activities to risk management to mitigate the negative impact of policy, natural, and market shocks. The modified allocation of resources and inputs usage can thus alter farm's returns and sustainability (Schmit and Roth, 1990). Therefore, we assume that in order to deal with shocks and uncertainties, farmers engage in proactive actions in the form of management strategies.

Borrowing from the RIMA framework and from risk theory, we model resilience as a function of five distinctive farms' characteristics, namely vulnerability, intensification, biodiversity, diversification and performance. These characteristics are the key dimensions/pillars that can be used to measure the farms' economic resilience to shocks, and they depend on the farmers' management strategies.

The five dimensions of farms' economic resilience were calculated using Farm Business Survey (FBS) data for England and Wales (Rural Business Research, 2017) from 2006-2015 (10 years). The FBS is funded by the UK Government's Department for Environment, Food and Rural Affairs (Defra) and the Welsh Government, and is the largest and most authoritative survey of the finances and performance of individual farm businesses in England and Wales. Detailed business accounts and general and physical characteristics for c.2,400 farms are collected annually, resulting in a database comprising over 2,000,000 data observations and more than 2000 raw and calculated variables. Other EU Member States have similar surveys collecting business and accountancy data, such as the Farm Accountancy Data Network (FADN), that would allow replication/comparative analysis of the work conducted in this study.

The population of the farms included in the FBS is sampled using a stratified approach into 14 farm types and 7 regions, with a uniform sampling rate within each stratum. FBS data used in this research was acquired under special licence from the UK Data Service[1].

FBS data are anonymised to prevent identification of individual farms, by removing disclosive information such as names, addresses and geographical coordinates. As a result, the lowest unit of geography reported is at county or unitary authority (UA) level. For those not au fait with the often-confusing world of British administrative geography, counties and UAs are the main units of local government in the UK. For this research, counties and UAs with low numbers of surveyed farms (<20) in each year of FBS were excluded from the analysis. A minimum sample size of 20 farms per geographical area was considered suitable for analysis, and was found to reflect the actual rural/urban geography of local government areas in England and Wales; that is, counties and UAs with an FBS sample size below 20 were found

[1] Department for Environment, Food and Rural Affairs and National Assembly for Wales, Farm Business Survey, 2006-2007: Special Licence Access [computer file]. Colchester, Essex: UK Data Archive [distributor], May 2008. SN: 5838 , http://dx.doi.org/10.5255/UKDA-SN-5838-1.

to be metropolitan areas with a low density of farms, whereas areas with a sample size of 20 or greater were predominantly rural. A map of the counties and UAs included in the analysis can be seen in Figure 1.

Each dimension of resilience was calculated using a combination of pre-calculated and raw variables from the FBS:

Vulnerability (*V*): Vulnerability was calculated as a percentage, based on the ratio of current liabilities to assets (liabilities / assets * 100). Liabilities comprised all current business liabilities, including mortgages, loans (bank, and family), leases, hire purchases, creditors and bank overdrafts. Assets included all agricultural land and woodland, buildings, machinery, crops, livestock, debtors, cash (at the bank and in hand), entitlement to basic payment scheme, and others. It is expected that an economically vulnerable farm – i.e. overexposed in terms of liabilities and therefore with less financial capacity to deal with unexpected shocks – will display a lower resilience to shocks.

Intensification (*I*): Calculated as the total input costs divided by the total area of utilised agricultural land. Input costs were extracted individually as raw variables from the FBS, and include costs associated with agricultural machinery (fuel, oil and running costs), electricity, fertilisers, crop protection, feed, and labour. A capital and input intensive farm is less flexible to adapt to financial and production conditions, as assets are highly specialized and productivity strongly depends on input availability. For example, if input prices dramatically increase, the farm's performance can decrease.

Biodiversity (*B*): The biodiversity of an individual farm was calculated using a Simpson Diversity Index applied to a matrix of crop types and crop areas for each farm. The matrix was constructed from SQL queries were used to extract data on individual crops for each farm from the FBS. The Simpson Diversity Index measures both the richness and evenness of the crops on a farm, where richness is the number crops types present on each farm, and evenness is the abundance of the different crop types, based on area. The resulting index is a value for each farm ranging from 0 to 1, where the greater the value, the greater the diversity. Higher crops biodiversity is expected to translate in higher farms' resilience, as it works as a portfolio insurance against extreme biotic or abiotic stresses (Matsushita, Yamane and Asano 2016), reducing the risk of yield variability and crop failure while improving average productivity (Di Falco and Chavas 2006).

Diversification (*D*): Diversification is the ratio between total farm income and the income from diversified (i.e. non-agricultural) activities, expressed as a percentage. Diversified activities include those associated with retailing, rents, tourism and catering, crafts, and power generation.. By horizontally (e.g. agro-tourism, livestock production) or vertically (e.g. process, distribute) diversifying the farm income, low revenues in some farming activities can be offset by higher revenues in other activities, stabilizing overall income (Meuwissen, van Asseldonk and Huirne 2008).

Performance (*P*): Calculated as the ratio between outputs (not including agricultural subsidies) and total business costs, expressed as a percentage. Outputs extracted from the FBS for use in this calculation included outputs from crops, livestock and diversified activities. Costs included a wide range of farm business costs, with an adjustment for unpaid labour. Farms with higher economic performance can benefit from higher returns and liquidity to face period of unfavorable production conditions.

Once the 'raw' resilience dimensions had been calculated, it was necessary to process and normalise/standardise the data, so that the dimensions could be combined to calculate a composite resilience index. This involved calculating the natural logarithm for certain dimensions with large values and data ranges (i.e. vulnerability, intensification, and performance) and then normalising each variable using the min-max method, so that each resilience dimension had a value in the range of 0 and 1. The final processing step involved converting the vulnerability and intensification resilience variables to negative values, as increases in positive values for these dimensions was thought to have a negative impact on resilience.

Geographic relationships across counties and UAs for each resilience dimension were analysed in R using Moran's I measure of spatial autocorrelation. Moran's I helps determine whether the data are positively, negatively or randomly correlated in space. The statistic reports a value between -1 and +1 where +1 is a perfect clustering of data (i.e. highly spatially autocorrelated) and -1 is perfect dispersal of data (i.e. highly spatially autocorrelated). A value of 0 means there is a completely random dispersal of values. The Moran's I statistics for the resilience dimensions can be seen in Table 2. Spatial autocorrelation of biodiversity and performance dimension values are positive, but weak. However, the data for vulnerability and intensification is more positively correlated, and the value for diversification (0.74) shows a very strong positive spatial autocorrelation of this reliance dimension, suggesting significant geographical clustering of this dimension.

The dimensions of economic resilience (*ER*) described above were used to compute a composite index of economic resilience (Economic Resilience Index, *ERI*), calculated as a standardized aggregation of the pillars as in (1) and (2):

$$ER_i = (-)V_i + (-)I_i + B_i + D_i + P_i \quad (1)$$

$$ERI_i = \frac{ER_i - ER_{min}}{ER_{MAX} - ER_{min}} \quad (2)$$

Where *i=1…..n* number of farms.

As a robustness check, the resilience index *ERI* was also calculated using the Coefficient Cronbach Alpha (*Alpha*) and two latent variable techniques, Factor Analysis (*FA*) and

Principal Component Analysis (*PCA*)[2]. The correlation between the four measures of *ERI* is always positive and statistically significant at 1% level, suggesting that *ERI* is robustly computed across different methodologies (Table 1).

Moran's I computed for the aggregated resilience index resilience (0.08) suggests a near-random distribution of resilience (Figure 3). Variation between and within counties/UAs was tested using ANOVA (F = 25.15, p < 2e-16), which suggested that the variation of resilience means among different counties is significantly larger than the variation of resilience within each county. Hence, we can conclude that for our confidence interval we accept the alternative hypothesis that there does appear to be a significant relationship between resilience and geographical units, as measured at county/UA level in England and Wales.

3. Econometric application of ERI

In what follows we develop an econometric application to illustrate the potential uses of the ERI index in empirical analyses. The application consists of estimating the impact of a series of factors exogenous to the farmer's decision making process – i.e. environmental, climatic and socio-economic factors - on the economic resilience of UK farms.

Such application provides interesting and original results related to the impact of environmental and climatic risks on farms' resilience and to the role of CAP subsidies and telecommunication infrastructure (representing two distinctive but key types of support for rural areas) in fostering the economic viability of farms.

[2] Details of the estimation of Alpha, FA and PCA are not included in this paper for length constraints reasons.

3.1 Econometric strategy and model specification

This section outlines the econometric strategy and empirical specification for estimating the potential impact of a variety of factors on the economic resilience of farms, using the Resilience Index developed in Section 2.

The factors to be tested empirically were the internal and external conditions under which farms operate; therefore we distinguish between farms' internal and external factors. Internal factors are those characteristics potentially affecting a farm's economic resilience, such as farmer's age and education, tenancy type and the amount of subsidies received from the government. The main difference between the internal factors and the pillars of economic resilience used for building the Resilience Index is that the latter are an outcome of the farmer's decision-making process, while the former are not. Therefore, internal factors, although inner to the farm, have a low degree of control by the farmer.

External factors are exogenous conditions under which the farmer operates, and they pertain to a higher level than the farm level, typically regional or country level. External factors are out of the control of the farmer as they are either environmental/climatic conditions, or outcomes of regional/national strategies such as the development of telecommunication infrastructure.

Internal and external factors constitute two different levels of drivers potentially affecting the farm's economic resilience: the farm-level and the county-level drivers. Therefore, in order to estimate the impact of internal and external factors on farms' economic resilience, we use two sets of data. Firstly, farm-level data from the UK FBS, and secondly, county-level data on environmental/climatic and telecommunication infrastructure conditions (see Section X).

In addition to this double-layered structure of the data, the FBS farm-level data have also a temporal dimension, clustering the farm's sample into ten waves (years) of repeated observations. Therefore, both the Resilience Index and the internal factors can vary from year to year and it is important to account for this additional layer as it represents a further level of potential dependency across observations (Azeem et al., 2016).

Given the multilevel structure of the data, the most suitable econometric approach to estimate the potential impact of different factors on the farms' economic resilience is multilevel modelling (or hierarchical modelling). This approach was initially proposed in the 1980s and it has been extensively developed since the early 90s by, for example, Bryk and Raudenbush (1992), Snijders and Bosker (1999) and, more recently, by Hox (2010).

The advantage of multilevel regression over OLS methods is to account for the hierarchical structure of data, which implies that the basic assumption of independence of observations is not satisfied. Moreover, multilevel regression methods combine the advantages of fixed effects (FE) panel data methods of controlling for omitted variables that vary across clusters and the advantages of random effects (RE) panel data methods of providing unbiased estimations of the impact of variables varying across clusters. This is done by a mixed model containing both FE and RE.

We design a three-level mixed model with individual farms *i* nested within waves (years) *j*, nested within counties *k*. The number of waves observed per farm varies between 2 and 10. The three-level design allows distinguishing between the effects of county-specific variables which refer to macro factors (telecommunication infrastructure, land diversity, flood, drought, water and wind erosion), and the effects of the farm-wave-specific values which refer to the changes taking place over time at farm level (age, type of tenancy and subsidies). The model is formally described in vector annotation:

$$y_{ijk} = \boldsymbol{X}_{ijk}\beta + \boldsymbol{Z}_{ij}\alpha + \boldsymbol{C}_{ik}\gamma + \varepsilon_{ijk} \qquad (3)$$

where $i = 1, \ldots, njk$ is the farm-level (first-level) observations nested within $j = 1, \ldots, mk$ wave-level (second-level) groups, which are nested within $k = 1, \ldots, m$ county-level (third-level) groups.

The fixed portion of equation (1) is the farm-level part $\boldsymbol{X}_{ijk}\beta$, which is directly estimated with standard OLS with β being the coefficients to be estimated.

As this is a three-level design model, we specify two RE equations: one for the wave-level $\boldsymbol{Z}_{ij}\alpha$ and one for the county-level $\boldsymbol{C}_{ik}\gamma$. Both are estimated indirectly through the variance components and the elements of the variance-covariance matrix. Therefore, a key step to fit the mixed model is the estimation of the variance components, that can be done with different methods (ANOVA, ML, REML).

The empirical mixed effect model to be estimated is the following:

$$ERI_{ijk} = \beta_0 + \beta_{1-5} \sum_1^5 Internal\ factors + \beta_{6-11} \sum_6^{11} External\ factors + \alpha_{0ij} + \gamma_{0ik} + \varepsilon_{ijk} \quad (4)$$

Where ERI_{ijk} is the resilience index calculated as the normalized sum of pillars 1 to 5 (see Section 2.1); the internal factors are farmers' *Gender* (=1 if male; 0 otherwise), *Age* (1 < 35; 2=35-45; 3=45-55; 4=55-65; 5=65-75; 6=75 >) and *Education* (1 School only;2 Apprenticeship; 3 GCSE or equivalent; 4 A level or equivalent; 5 College / National Diploma; 6 Degree; 7 Postgraduate), type of *Ownership* (=1 if owner occupied; 0 if tenanted or mixed) and a relative measure of *Subsidies* calculated as the sum of farm CAP subsidies on the farm business output. All data for internal factors are from ten waves of the FBS, from 2006 to 2015.

The external factors are summarised in Table 3, along with a brief description of the methodology and main datasets used to produce them. These factors are mainly natural, such as environmental and climatic conditions, and socio-economic, such as subsidies and infrastructures.

Among the environmental factors, soil erosion due to water and wind, and land use diversification were selected. Erosion can affect farms' resilience in the long term as it can deplete the main natural resource used for the agricultural activity – i.e. soils. The diversification of land use has been highlighted in the literature as a key element for the resilience of farms' returns (e.g. Di Falco et al., 2010; Abson et al., 2013; Matsushita et al., 2016). The land cover data used to extract agricultural land was the Land Cover Map 2007 1km^2 raster (grid) spatial dataset produced and distributed by the UK's Centre for Ecology and Hydrology (CEH)[3].

Two variables of climatic risks have been selected, *Flood* and *Drought*, both with the potential of increasing farms' vulnerability and reducing their performance.

Regarding socio-economic conditions, on the one hand "safety nets" in the form of public support (i.e. CAP subsidies) are particularly important as they can reduce the negative impacts of market risks by stabilizing farm income (Meuwissen et al., 2008). On the other hand, provision of telecommunication infrastructure, especially of *Broadband* in rural areas, is a key element for farmers to obtain up to date and fast information on markets and farming practices for modern agriculture, in reaction to market and/or production risks and uncertainties (Just et al., 2003).

The above external factors were calculated for each of the counties and UAs selected for analysis, based on the FBS sample size threshold (see Section 2). For these variables the management, analysis and visualisation of spatial data was conducted using QGIS open source geographical information systems (GIS) software. Geospatial boundary data for counties and UAs in England and Wales were downloaded from the Ordnance Survey OpenData website[4]. Figure 4 shows an example of an exogenous factor, "safety nets", mapped by county/UA.

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[3] - https://www.ceh.ac.uk/services/land-cover-map-2007

[4] https://www.ordnancesurvey.co.uk/business-and-government/products/boundary-line.html

Model (2) is a random intercept model, where the intercepts α_{0ij} and γ_{0ik} are the only coefficients allowed to vary randomly – i.e. the average economic resilience is allowed to vary randomly across waves and across counties – and the effects of the random intercepts are estimated with maximum likelihood estimators.

For comparison and robustness check purposes, model 2 is also estimated with OLS and FE. Finally, model 2 is estimated: i) for the whole sample of farms encompassing all farm types; ii) for each sector (i.e. livestock grazing, dairy, cereals, horticulture, poultry and pigs), assuming that the drivers of economic resilience are different for different farm types as they can be more or less affected by environmental/climatic and telecommunication infrastructure conditions; iii) for each pillar of economic resilience (i.e. vulnerability, intensification, biodiversity, diversification and performance) as each driver can have a different impact on the pillars.

3.2 Results of econometric application of ERI

Table 4 shows the main results of the mixed effects estimation of model (4) on the entire sample of FBS farms for 2006-2010. The first three columns show the results of the impact of internal and external factors on farms' economic resilience measured with the ERI developed in Section 2. Three different methods have been applied as a robustness check of model (4): pooled OLS, FE model and mixed effects model. Model (4) proved to be robust across the three different estimators, with most of the standard errors being higher in column 3, as expected.

Given the multilevel structure of our data, we consider the mixed effect estimator the most appropriate one. In column three, all the internal factors (*Gender*, *Age*, *Education* and type of tenancy *Ownership*) are highly significant, confirming the important role of these factors in driving farms' economic resilience. Notably, *Age* and *Education*, which are related to higher experience and managerial skills respectively, have a positive and significant impact, suggesting that farms' economic resilience can be higher in farms managed by more experienced and farmers with more developed management skills However, the coefficient magnitude is rather low.

Interestingly, *Subsidies* have a negative impact on ERI, with a much larger coefficient significant at 1% level. This suggests that the way British farms have been supported by the CAP in the last ten years, while providing important benefits in terms of diversification and farm's performance (columns 7 and 8 respectively), does not effectively improve the vulnerability and sustainability of farms (columns 4-6) and that, overall, higher *Subsidies* can lead to lower economic resilience.

Regarding the external factors, Table 4 shows clearly that farms located in counties with more diversified land use (*Land diversity*) have a higher and 10% significant resilience, significantly reducing farms vulnerability and inducing more diversification which is a viable management strategy against production and market risks (Vigani et al. 2015). This result is in line with studies on agrobiodiversity and agroecosystems management (e.g. Quaas and Baumgartner, 2008; Di Falco et al., 2010; Matsushita et al., 2016).

Among the environmental factors, in our analysis soil erosion is the most important factor potentially affecting economic resilience. This result is in line with an extensive literature that underlines the importance of soils health for the agricultural activity (see Lal, 2015, for a review of this literature). More specifically, in the British context, *Wind erosion* seems to have a negative impact on farms ERI, increasing farms vulnerability and reducing opportunities of diversification. *Water erosion* has a negative impact on the diversification dimension but not on economic resilience, and, also a positive impact on farms' intensification, as more intensive farms have lower opportunities to reallocate assets towards diversified activities. The positive and significant impact of *Water erosion* on performance is difficult to explain, a part of the fact that it has the same direction of the impact on intensification. There are probably other effects, most likely nonlinear, that should be considered and further explored.

In the introductory section it was recognized that resilience is context-specific. Resilience dimensions and outcomes depend strongly on the type of resources used in the agricultural production activities. Resource use varies significantly across different types of farms and especially across agricultural sectors. Some sectors are more dependent on land and climate, such as grazing, cereals and horticulture, while others are more input and labour intensive, such as dairy, poultry and pigs. We assess differences across agricultural sectors by running model (4) with the mixed effects estimator for each agricultural sector in England and Wales (table 5).

Table 5 confirms that *Age* and *Education* are important internal drivers, increasing economic resilience in the grazing, dairy, cereals and poultry sectors.

Higher levels of *Subsides* show a negative and significant impact on economic resilience for the majority of the sectors, but with two important exceptions, grazing livestock and pigs. The fact that the type of CAP support of the last decade had a positive economic resilience impact in these two sectors but negative on the other sectors, highlights the different sectorial impact and benefits that the CAP has.

A richer agrobiodiversity of the agricultural systems, measured buy the *Land diversity* index, is associated with higher economic resilience of grazing livestock and cereals farms. As these two sectors are highly dependent on land as a resource, it is not surprising that the buffering role of agrobiodiversity to shocks is a critical component of these farming systems.

With regard climate variables, the positive impact of *Floods* on grazing and dairy is quite counterintuitive. However, it is worth noting that grazing livestock and dairy are among the least affected sector by floods, therefore further nonlinear effects should be tested.

Interestingly, *Drought* is a threat for economic resilience of cereal farms alone. Indeed, cereal farms are the most affected by water scarcity and they are mainly located in large flat areas, such as the East of England, that in the last ten years have experienced the most of the reduction in water availability.

Finally, in terms of the sectorial analysis of resilience drivers, the pig sector shows the greatest differences. This is not surprising giving its peculiarities in terms of use of natural resources and managerial management. The pig sector is highly intensive with a highly integrated supply chain. This might explain the fact that younger and more educated farmers are associated with a higher economic resilience of the sector. It is also important to note that this sector is the only one displaying a positive impact of *Broadband* on its economic resilience. The arrangements in the pig supply chain along with the volatility of the input and product markets require more efficient and fast telecommunication infrastructure, in order to obtain updated information on the changes of the market structure and promptly react accordingly. Therefore, a well-functioning *Broadband* system in rural areas where pigs are more intensively produced reduces the producers' remoteness to the markets and can allow higher resilience.

4. Conclusions

This paper presents preliminary results of an ongoing research aiming to contribute to the current agricultural economics literature attempting to operationalize and estimate resilience and its potential determinants.

Building on previous literature, the paper identifies five pillars that can be used to define the dynamic and multidimensional nature of the economic resilience concept at the farm level. These pillars are farms' vulnerability, intensification, biodiversity, diversification and performance. By using proxy variables for each pillar, an index of farms' economic resilience has been developed for English and Welsh farms. An analysis of the spatial correlation economic resilience showed that the distribution of the resilience index is significantly correlated with the geographical dispersion, suggesting that environmental and local factors are key elements of farms' economic resilience.

In a second step, the economic resilience index is used to assess the impact of a series of farms' internal and external factors on economic resilience. Given that the external factors, which are climatic, environmental and telecommunication infrastructure factors, are exogenous to the farms' decision-making process, a hierarchical mixed effects model has been used.

The results of the model indicate that the CAP subsidies of the last ten years have had a negative impact on farms' economic resilience in UK, especially for the cereals, horticulture, poultry and dairy sectors. A more diversified land use reduces farms' vulnerability providing more opportunities for agricultural diversification, especially for the most land intensive sectors such as grazing livestock and cereals.

It has also emerged that soil health is a key driver of farms' economic resilience, as soil erosion due to either wind or water drastically reduces resilience. The same applies to drought risks.

Extensive telecommunication infrastructure in the form of broadband in rural areas has a particularly important role in the economic resilience of the pigs sector, which is characterized by integrated vertical relationships and intensive farming systems.

These preliminary results are not only relevant for farmers and their management decisions, but also for policymakers and the overall policy discussions towards a revised CAP post 2020, where it is foreseen an increased role for risk management policies and resilience.

However, further research on how to effectively measure farms economic resilience is needed and is currently ongoing, as well as a better understanding of the resilience drivers, internal and external the farming system.

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Figure 1. Counties and unitary authorities of England and Wales included in the research.

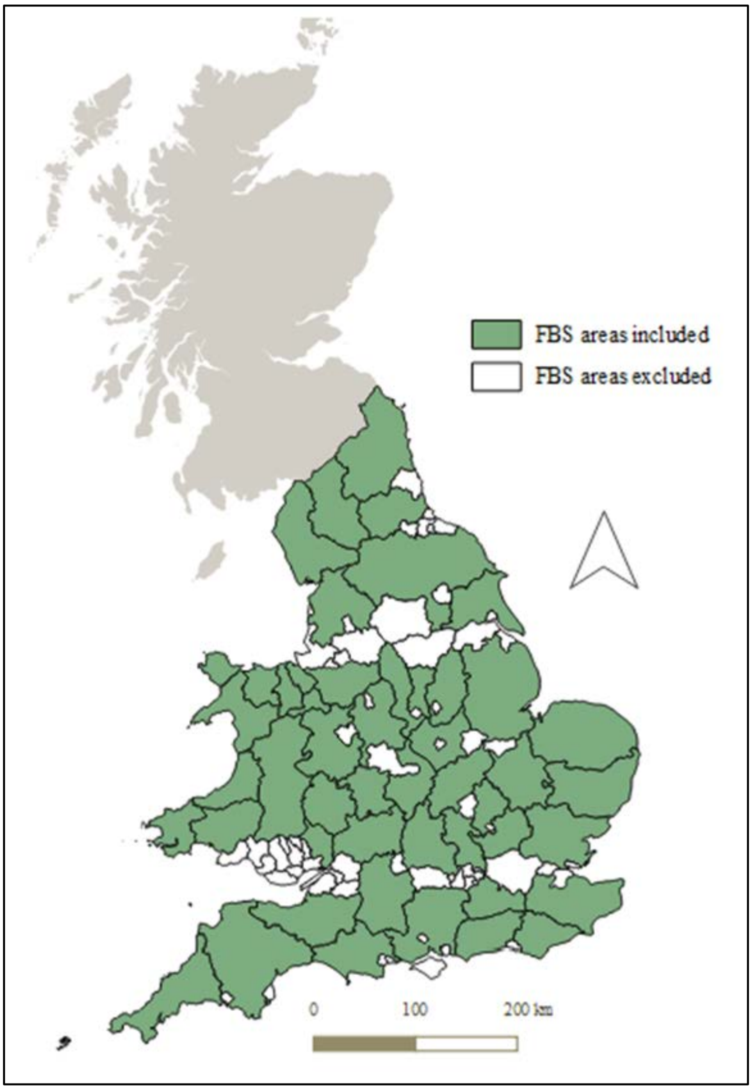

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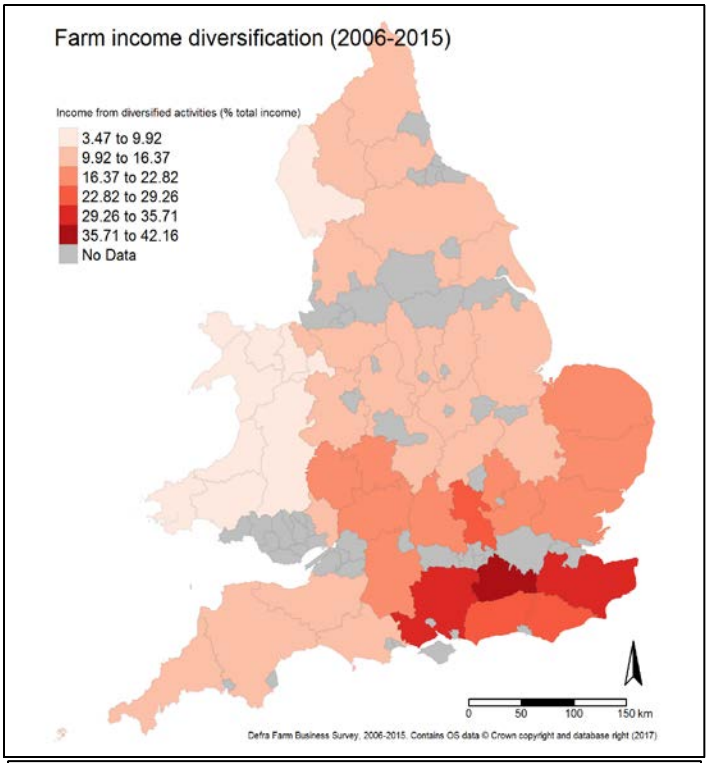
Figure 2. Maps highlighting the differences in spatial autocorrelation between two resilience dimensions; diversification (top – Moran's I = 0.74) and performance (bottom - Moran's I = 0.16)



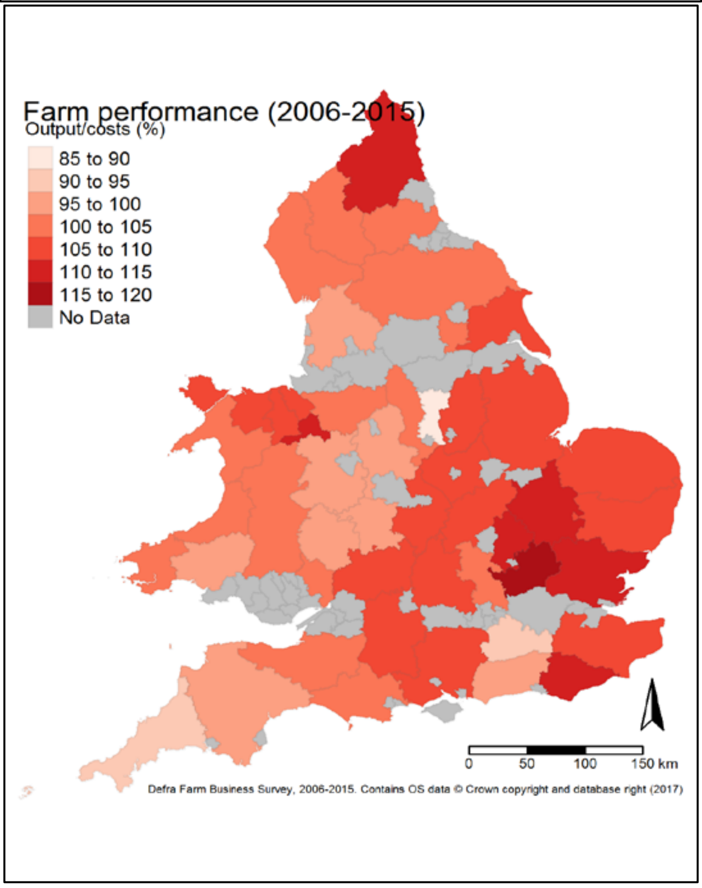


Figure 3. Aggregated resilience index mapped at county/UA level for England and Wales

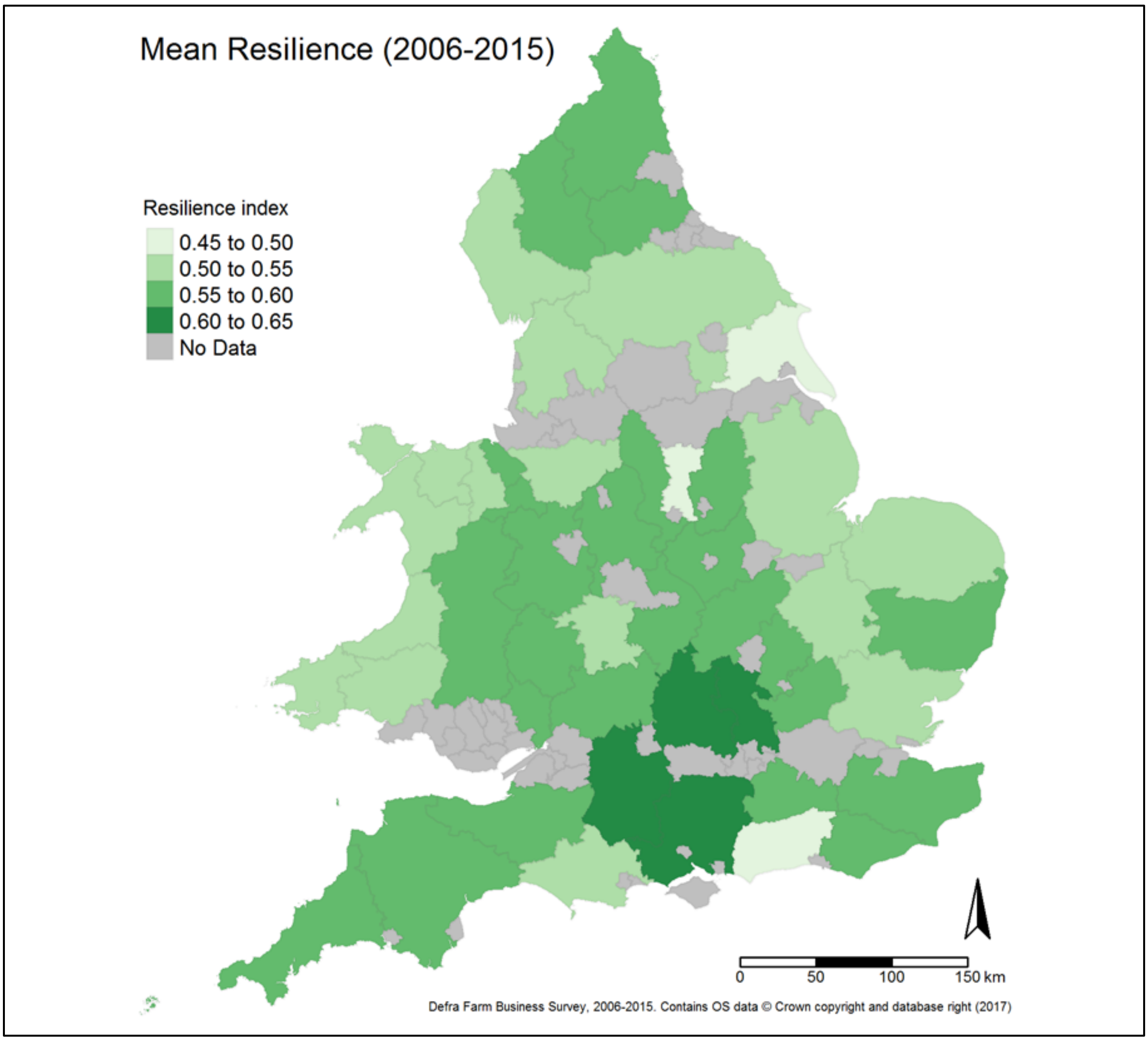
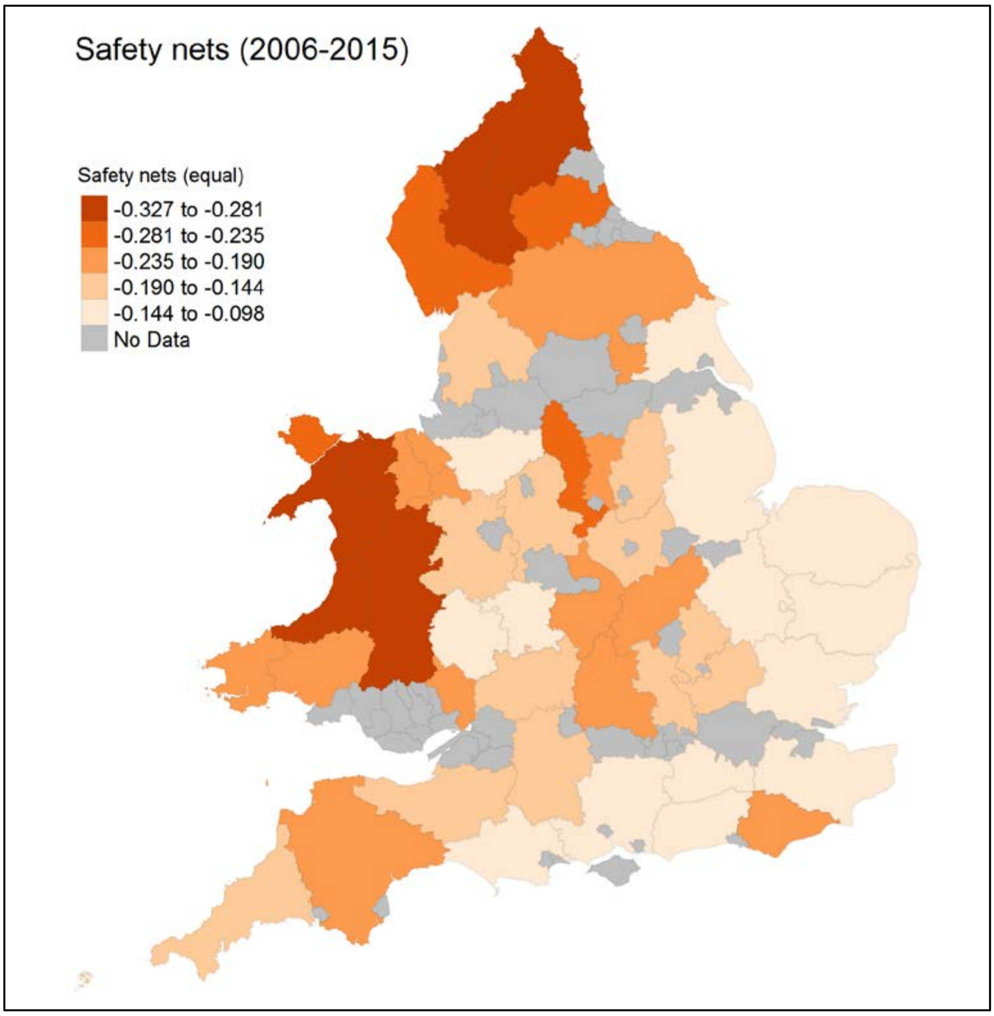


Figure 4. "Safety nets" mapped by county/UA in England and Wales. The darker the hue, the higher the proportion of farm income from subsidies



Tab. 1: Correlation of ERI indexes calculated through different methods.

Computation method of ERI	Normalized aggregation	Factor Analisys	Principal Component Analysis	Cronbach Alpha
Normalized aggregation	1			
Factor Analisys	0.4941*	1		
Principal Component Analysis	0.4941*	1.0000*	1	
Cronbach Alpha	0.3499*	0.8968*	0.8968*	1

*Note: * indicate correlations significant at the 1% level.*

Table 2. Moran's I spatial autocorrelation scores for the different resilience dimensions

RI Pillar	Moran's I score	p-value
Vulnerability	0.37	6.97E-05
Intensification	0.37	8.26E-05
Biodiversity	0.21	0.01208
Diversification	0.74	7.11E-14
Performance	0.16	0.03622

Table 3. Exogenous conditions potentially affecting the farms' economic resilience

Variable	**Description**
Soil erosion by water	Average soil erosion by water on agricultural land per county (T/ha^2). Calculated from the RUSLE (EU) dataset: http://esdac.jrc.ec.europa.eu/content/soil-erosion-water-rusle2015
Soil erosion by wind	Average soil erosion by wind on agricultural land per county (T/ha^2). Calculated from the RUSLE (EU) dataset: http://esdac.jrc.ec.europa.eu/content/Soil_erosion_by_wind
Flooding	% of agricultural land in each county where the chance of flooding in any year is greater than or equal to 1 in 75 (1.3%). Calculated using data from the UK Environment Agency and the Welsh Government: https://data.gov.uk/dataset/flood-risk-areas http://lle.gov.wales/catalogue/item/Rofras/?lang=en
Drought (1 year)	% of agricultural land in each county that experiences at least one extreme 1-month drought per year. Data from: https://eip.ceh.ac.uk/droughts
Drought (10 year)	% of agricultural land in each county that experiences at least one extreme 1-month drought per year – averaged over 10-year study period. Data from: https://eip.ceh.ac.uk/droughts
Broadband speed	Broadband speed (Mbps) for rural areas of individual counties, derived from Ofcom 2015 postcode-level broadband data
Safety nets	Income from subsidies and agri-environment schemes as a percentage of total farm income, averaged for each county. Data from the FBS.

Table 4. Results of the mixed effects model to estimate the impact of internal and external conditions on farms' resilience and its dimensions.

	Resilience Index			P1	P2	P3	P4	P5
	OLS	FE	ME	Vulnerability	Intensification	Biodiversity	Diversification	Performance
Farm-level variables								
Gender	-0.0440***	-0.0280***	-0.0101**	-0.0275***	-0.0109***	0.0585***	-0.061***	0.020***
	(0.003)	(0.002)	(0.004)	(0.004)	(0.002)	(0.008)	(0.006)	(0.001)
Age	0.0125***	0.0292***	0.00744***	0.0162***	-0.0027***	-0.004**	0.014***	0.0002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.0005)	(0.001)	(0.002)	(0.0003)
Education	0.00435***	0.00973***	0.00267***	-0.000846	-0.00251***	0.002**	0.008***	0.003***
	(0.0001)	(0.001)	(0.0005)	(0.001)	(0.0003)	(0.001)	(0.001)	(0.0002)
Ownership	-0.00886***	0.00696*	-0.00602***	0.0818***	-0.0238***	-0.070***	-0.001	-0.005***
	(0.002)	(0.004)	(0.002)	(0.002)	(0.001)	(0.003)	(0.004)	(0.001)
Subsidies	-0.212***	0.0839***	-0.254***	-0.277***	-0.514***	-0.0846***	0.074***	0.026***
	(0.005)	(0.015)	(0.006)	(0.008)	(0.003)	(0.011)	(0.012)	(0.002)
County-level variables								
Broadband	0.00824	-0.0613	0.003	-0.004	-0.006	-0.016	0.0323	-0.004
	(0.005)	(0.047)	(0.020)	(0.019)	(0.012)	(0.046)	(0.037)	(0.007)
Land diversity	0.0218***	0.0817**	0.0232*	-0.0260**	-0.007	0.014	0.0933***	-0.005
	(0.003)	(0.041)	(0.014)	(0.013)	(0.008)	(0.032)	(0.026)	(0.005)
Flood	0.0156***	-0.030	0.0256	0.019	-0.003	0.009	0.041	0.009
	(0.005)	(0.076)	(0.016)	(0.016)	(0.010)	(0.038)	(0.031)	(0.006)
Water erosion	0.00144	-0.008***	-0.0171	-0.007	0.0121***	-0.041	-0.022**	0.008***
	(0.004)	(0.003)	(0.011)	(0.006)	(0.003)	(0.029)	(0.010)	(0.002)
Wind erosion	-0.0489***	0.0461	-0.0723***	0.0406**	0.006	-0.066	-0.205***	0.003
	(0.004)	(0.059)	(0.020)	(0.019)	(0.012)	(0.045)	(0.038)	(0.008)
Drought	-0.0265***	-0.126*	-0.025	-0.0205	-0.007	-0.03	-0.025	0.005
	(0.005)	(0.070)	(0.021)	(0.020)	(0.013)	(0.050)	(0.040)	(0.008)
_cons	0.482***	0.407***	0.471***	-0.350***	-0.507***	0.619***	0.085**	0.742***
	(0.007)	(0.052)	(0.019)	(0.018)	(0.011)	(0.043)	(0.035)	(0.007)
County var(_cons)			0.0004	0.0006	0.0003	0.0019	0.0023	0.0001
County-year var(_cons)			0.0023	3.94E-19	2.50E-05	0.0184	0.0005	4.13E-05
var(Residual)			0.0176	0.0298	0.0051	0.0482	0.0654	0.0022
N (Individuals)	22906	22906	22906	22906	22906	22906	22906	22906
N (Counties)	49	49	49	49	49	49	49	49
N (County-years)	488	488	488	488	488	488	488	488
R-sq	0.072	0.055						

Notes: Statistical significance at the 99% (***), 95% (**) and 90% (*) confidence levels. Robust standard errors in parenthesis.

Table 5. Results of the mixed effects model by type of farm.

	Grazing	Dairy	Cereals	Horticulture	Poultry	Pigs
Farm-level variables						
Gender	-0.016***	-0.043***	-0.043***	-0.021*	-0.061***	0.011**
	(0.005)	(0.010)	(0.006)	(0.012)	(0.017)	(0.005)
Age	0.007***	0.010***	0.005***	0.024***	0.011**	-0.005***
	(0.001)	(0.002)	(0.002)	(0.004)	(0.005)	(0.002)
Education	0.003***	0.006***	0.003***	-0.001	0.006*	0.003***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.003)	(0.001)
Ownership	0.024***	0.016***	0.040***	0.007	0.0136	-0.007*
	(0.003)	(0.004)	(0.004)	(0.009)	(0.0136)	(0.004)
Subsidies	0.018**	-0.230***	-0.119***	-0.70***	-2.229***	0.165***
	(0.008)	(0.035)	(0.023)	(0.055)	(0.129)	(0.028)
County-level variables						
Broadband	-0.001	-0.008	-0.001	0.037	0.0182	0.038*
	(0.026)	(0.028)	(0.025)	(0.067)	(0.091)	(0.023)
Land diversity	0.045**	0.030	0.054***	0.075	0.069	0.004
	(0.019)	(0.019)	(0.016)	(0.055)	(0.056)	(0.016)
Flood	0.039*	0.0436**	0.023	0.064	0.049	-0.004
	(0.022)	(0.022)	(0.020)	(0.062)	(0.066)	(0.020)
Water erosion	-0.047***	-0.004	-0.008	-0.002	-0.055**	-0.004
	(0.017)	(0.017)	(0.007)	(0.014)	(0.025)	(0.006)
Wind erosion	-0.065**	-0.081***	-0.073**	-0.249**	-0.034	-0.010
	(0.028)	(0.026)	(0.033)	(0.126)	(0.134)	(0.038)
Drought	0.012	-0.040	-0.060**	0.017	0.018	-0.004
	(0.03)	(0.028)	(0.023)	(0.066)	(0.065)	(0.018)
_cons	0.508***	0.472***	0.570***	0.226***	0.250***	0.744***
	(0.025)	(0.026)	(0.025)	(0.073)	(0.082)	(0.026)
County var(_cons)	0.0008	0.0007	0.0010	0.0049	0.0048	0.0003
County-year var(_cons)	0.0040	0.0026	0.0001	5.06E-20	0.0002	1.88E-27
var(Residual)	0.0100	0.0099	0.0110	0.0296	0.0178	0.0011
N (Individuals)	8870	3994	3320	1878	573	480
N (Counties)	49	48	44	33	34	28
N (County-years)	487	451	403	291	228	209

Notes: Statistical significance at the 99% (***), 95% (**) and 90% (*) confidence levels. Robust standard errors in parenthesis.