Extended Abstract

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Paper/Poster Title	Farms and their neighbours. Analysis of spatial dependencies in the Hungarian agriculture

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Abstract	*200 words max*
In this research, we assume that farm technology and its changes are empirical learning processes, where farms are influenced by the example of their neighbours. That is, we focus on spatial dependencies in the Hungarian agriculture. To do so, we analyse the spatiality of more biodiverse farms, the spatiality of participation in agri-environmental schemes and the spatiality of farm technical efficiency. We use an advanced classification scheme to identify the more biodiverse and low input using farms. Preliminary results are mixed. On one hand, more bio-diverse farms tend to cluster together, yet this seems to be only partially explained by a learning process in space. With respect to participation in agri-environmental schemes we do not find spatial dependencies. Further, there is only mild evidence that more technical efficient farms are clustering together. We formulate some policy implications, most notably emphasising the inefficiency of agri-environmental schemes with respect to their original goals.	

Keywords	e.g. Bioenergy, Energy Efficiency
JEL Code	e.g. Energy: Demand and Supply Q41 see: www.aeaweb.org/jel/guide/jel.php?class=Q)

Introduction	*100 – 250 words*

Tobler's first law of economic geography states:
'Everything is related to everything else, but near things are more related than distant things', Tobler (1970, p. 236). Therefore, one would expect – since changing or ameliorating farming technology, applying for Agri-Environmental payments (AES) are simultaneously a theoretical and empirical a learning processes, where good (or indeed best) practice examples should influence decisions of neighbours – that spatial distribution of the more biodiverse, more efficient, and more engaged into AES schemes farms are not random.

Thus, in this research we aim to test the following three hypotheses:
Hypothesis 1: There are spatial dependencies amongst more biodiverse farms, i.e. innovative farms cluster together
Hypothesis 2: There are spatial dependencies amongst farms with increased uptake of AES payments, i.e. there is a learning or imitation process amongst farmers.
Hypothesis 3: There are spatial dependencies with respect to measured farm technical efficiency, i.e. efficient farms cluster together

Following Rogers (1995), one may assume that innovative farmers adopt unconventional farming systems earlier, and then innovation is diffused by local networks or imitation process. In our research we will consider both more biodiverse farming systems and participation in AES as innovation.

The literature applying spatial econometrics techniques is relatively new, nonetheless because corresponding tests and models were only recently incorporated into statistical software packages. Not surprisingly - since the objective is relatively easy to grasp with a clear incentive, that is, Measure 214, sub-measure A1 - the bulk of scientific literature focuses on organic farming, more precisely analysing the decision of conversion in the light of spatial heterogeneity and spatial dependence on various territorial levels. Thus, Schmidter et al (2012) elaborates a theoretical model of organic farming adoption and tests the framework using German county level data, Bartolini et al. (2014) focuses on farm participation in modernisation of agricultural holdings program, Yang et al. (2014) analysis farmer participation in bird and habitat conservation in Scotland, Boncinelli et al. (2015), discusses participation pattern in agro-environmental payments in Tuscany and finally, Läpple and Kelley (2015) find that neighbouring Irish organic drystock farmers exhibit a similar choice behaviour.
The most recent, and closest to our research aim papers are Capitano et al. (2016) focusing on CAP payments induces spatial diversity n cereal crops and o Bartolini and Vergamini (2019) on spatial agglomeration of AES in Tuscany using both micro and meso-level characteristics. All the papers quoted in the non-exhaustive literature review above, did find significant spatial effects, and concluded that either the spatial lag or the spatial error model was superior to OLS.

Further we test the spatial distribution of farm technical efficiency and to answer the question whether more efficient farms tend to cluster together. With the evolution of spatial econometrics, in the past decade a number papers incorporated spatial dependencies into the classical technical efficiency estimations: Fusco and Vidoli (2013) propose a theoretic framework for incorporating spatial effects, Vidoli et al. (2016) emphasises the importance of local business climate with respect to the efficiency of Italian wine producers, and most recently Tsukamoto (2019) takes the by now classical Battese and Coelli (1995) panel efficiency model further and incorporates spatial autoregressive elements.

Methodology	***100 – 250 words***

A key issue of the analysis in the choice of data to be used. European agricultural economist's first thought would be using data from Farm Accountancy Data Network. However, the number of organic farms is very limited in FADN. And focusing only on certified organic farms would unnecessarily restrict our sample. Thus, we use the farm typology developed by the LIFT H2020 project, that identifies Low Input Farms taking into consideration a multitude of variables (https://www.lift-h2020.eu). To obtain a better perspective with respect of agglomeration effects of biodiverse farms, we also use agricultural census data.

With respect to the methodology, spatial location theory was originally developed by Thünen (1910), through a model assuming non-zero transportation costs, where agricultural production is organized in concentric circles around consumer hubs - depending on the perishability of goods produced, their relative price and land rents. More recently, the work of Anselin (1988) resulted in directly estimable and testable spatial econometric models whilst amongst others Krugman (1996) applied the theory of economic geography to explain the agglomeration effects of industries. Besides logistics, local knowledge, the proximity of markets, some harder- to- grasp drivers explaining agglomeration or clustering effect at farm level include: good example or conduit following (e.g. hillside Honduras farmers more likely convert to organic agriculture if their neighbors did, see Wollni and Andersson 2014), information sharing (e.g. spatial dependence of organically managed land in Germany, see Bichler et al. 2005 and Schmidtner et al. 2014), reduced transaction costs (e.g. the French territories where organic farming is already present have the highest conversion rates, see Allaire et al., 2015).

By now, most econometric software packages are capable to some level of spatial data analysis To reveal the possible spatial relationships in the data, the Exploratory Spatial Data Analysis (ESDA) is performed resulting in the calculation of Local Indicators of Spatial Association (LISA) and Moran's I statistic (see e.g. Anselin 1995 and Anselin et al. 1996). Estimating technical efficiency scores in a non-spatial model will result in biased estimates shold there be spatial autocorrelation. Thus, instead a two-step method (estimate TE using one of the classical models and then test for spatial autocorrelation or clustering of the scores) we follow the Tsukamoto (2019) panel efficiency model that incorporates spatial autoregressive elements as well.

Results	***100 – 250 words***

Preliminary results are available at this point. The clustering of biodiverse farms cannot be rejected, based on the agricultural census data. It seems however – and we are still working on it – that it is largely dependent of the crops produced. And a closer examination reveals, that (at least) in some cases, agglomeration effects are more due to microclimatic conditions, or the regions' specific traditional crop-mix, and production technology, rather than to spatial effects due to a learning process. With respect to the hypothesis that more efficient farms are clustering together, our results are mixed, and largely dependent on the type of output.

Discussion and Conclusion	*100 – 250 words*
Based on preliminary results, we observe clustering of more biodiverse farms, that is, a knowledge spillover with respect to reduced agricultural input use. Further, there is only very mild evidence, that participation in the AES induces more farm biodiversity. Our results suggest that more biodiverse farm clusters and farms with higher AES uptake do not spatially overlap. A rather summary and based on first results preliminary conclusion would be the higher importance of farm knowledge diffusion networks with respect to spreading farm biodiversity, compared to the top down policy induced incentives in this respect.	