# DOES AGGREGATION AFFECT INFERENCES, WHEN ANALYSING THE ADOPTION OF AN EMERGING ALTERNATIVE CROP? A COMPARISON OF FARM- AND MUNICIPALITY-LEVEL RESULTS FOR CULTIVATION OF THE STYRIAN OIL PUMPKIN

Andreas Niedermayr and Jochen Kantelhardt

a.niedermayr@boku.ac.at

Institut für Agrar- und Forstökonomie, Universität für Bodenkultur Wien, Feistmantelstraße 4, 1180 Wien, Österreich



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Andreas Niedermayr\* and Jochen Kantelhardt\*

\*Institute of Agricultural and Forestry Economics, University of Natural Resources and Life Sciences, Vienna

### **Summary**

The aim of this study is to assess, whether estimation of the same innovation-adoption model at farm- and municipality-level results in an ecological fallacy, meaning that based on aggregated data, one would make inverse inferences about the driving forces influencing the adoption decision at the farm level. The adoption of an emerging alternative crop in Austria, the Styrian Oil Pumpkin, serves as an applied example. Our findings indicate the presence of an ecological fallacy. We therefore propose further research, which could consist of Monte Carlo simulations in order to analyse sensitivity of results with respect to the degree of aggregation.

### Keywords

Innovation adoption, ecological fallacy, SLX-Tobit model, Styrian Oil Pumpkin, PGI.

### 1 Introduction

Empirical innovation adoption studies are interested in estimating the effect of various driving forces on the adoption of innovations. As innovation adoption often occurs in spatial clusters, the notion of spatial spillover effects (e.g. presence of factors that facilitate the adoption of an innovation in one place also affect adoption in nearby places) is of particular interest in this context. In order to analyse such spillover effects, spatially explicit data of the whole population of interest (e.g. farms) is needed. As complete census data at the farm level is hardly available and limited resources prevent large-scale surveys of the whole farm population, researchers mostly use aggregated data (e.g. Schmidtner et al., 2012; Garrett et al., 2013; Niedermayr et al., 2016). However, this approach may result in an "ecological fallacy" (Openshaw, 1984; Anselin, 2002), meaning that the usage of aggregated data to make inferences about a process that happens at the farm level (the adoption decision) may lead to inverse inferences about the true relationship of interest. While limited research that compares the outcomes of such studies at different aggregation levels exists (e.g. Schmidtner et al., 2015), we are not aware of any empirical analysis comparing aggregated- and farm-level results. The aim of this study is therefore to assess, whether aggregation could lead to an ecological fallacy. The adoption of oil-pumpkin cultivation in an Austrian case study region serves as an applied example.

### 2 Data and Methods

For the regression analysis, we use previously unavailable, spatially explicit cross-sectional data from 2010 of 7,726 farms in a case study region in Lower Austria (BMLFUW, 2016), where the implementation of a protected geographical indication for Styrian Pumpkin Seed Oil triggered a dynamic development of oil-pumpkin cultivation (Niedermayr et al., 2016). Because of censoring in our dependent variable (share of arable land, cultivated with oil pumpkin), we estimate a Tobit model and extend it to a Spatial Lag of X (SLX) Tobit model. In a SLX model, spatial lags of the independent variables, reflecting for each observation the average value of the respective independent variable of neighbouring observations, are added as further independent variables. This allows estimating potential spillover effects of the independent variables on adoption (Halleck Vega and Elhorst, 2015), reflecting e.g. shared usage of

resources for oil-pumpkin cultivation. The independent variables in our model describe natural conditions, availability of oil-pumpkin specific infrastructure, production- marketing- and policy- related factors, social, temporal and spatial factors. We directly aggregate the farm-level data to the municipality-level, in order to rule out any other sources of influence on the results.

### **3** Preliminary results

Table 1 shows the partial effect at the average (PEA) of the independent variables. While most signs of the significant variables do not change, when comparing municipality- and farm-level results, there are also differences. We briefly illustrate the issue with the variable direct marketing, while noting that a similar line of argument is also possible for others (e.g. the spatial lag variables). Although, direct marketing is beneficial for oil-pumpkin cultivation from a theoretical point of view, the model based on municipality-level data shows a negative relationship. Most likely, at the municipality level, the presence of direct marketing farms, which do not cultivate oil pumpkin, leads to a bias of the true relationship of interest. Such potential ecological fallacies could also be present in comparable studies and are in our case overcome by an analysis at the farm-level. However, the scarce availability of spatially explicit farm-level data is not likely to change in the near future, ruling out this option as a general solution. We therefore propose further research, which could include Monte Carlo simulations in order to analyse the sensitivity of results with respect to the degree of aggregation.

Table 1. Comparison of marginal effects at the municipality- and farm level							
Independent Variables	Municipality level Farm leve			level			
Soil-quality index	0,04	n.s.	0,01	***			
Distance to nearest drying facility for pumpkin seeds	-0,20	***	-0,10	***			
Livestock density	-0,11	*	-0,01	**			
Log(farm size)	-0,010	*	-0,003	**			
Log(UBAG subsidy for arable land)	-0,000	n.s.	0,000	n.s.			
Log(arable land)	0,005	n.s.	0,006	***			
Temporal lag of oil-pumpkin share	1,00	***	0,09	***			
Direct marketing	-0,06	*	0,15	*			
Organic farming	0,09	***	0,95	***			
Agricultural education	0,03	**	0,08	*			
WX of Direct marketing	-0,05	n.s.	-0,39	n.s.			
WX of Organic farming	0,003	n.s.	0,45	**			
WX of Agricultural education	-0,01	n.s.	0,34	*			

Table 1: Comparison of marginal effects at the municipality- and farm level

Source: own calculations, data from BMLFUW (2016). Note: the PEAs of the three log-transformed independent variables have been divided by 100 so that a change of x by 1% can be interpreted as a percentage-point change of y; the 3 variables "direct marketing", "organic farming" and "agricultural education" are shares of all farms/farmers at the municipality level and dummy variables at the farm level; spatial-lag variables are denoted by the prefix "WX of"; \*\*\*, \*\* and \* and denote significance at the 1%, 5% and 10% levels. n.s.=not significant

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University of Natural Resources and Life Sciences, Vienna



Andreas Niedermayr Institute of Agricultural and Forestry Economics Feistmantelstrasse 4 A-1180 Vienna; Austria Phone: +43 (1) 47654-73319 E-Mail: a.niedermayr@boku.ac.at



XV EAAE Congress

Towards Sustainable Agri-Food Systems: Balancing between Markets and Society

# DOES AGGREGATION LEAD TO BIASED INFERENCES? AN EMPIRICAL ANALYSIS OF THE ADOPTION OF OIL-PUMPKIN CULTIVATION IN AUSTRIA AT THE FARM- AND MUNICIPALITY LEVEL

#### Andreas Niedermayr\* and Jochen Kantelhardt\*

\*Institute of Agricultural and Forestry Economics, University of Natural Resources and Life Science, Vienna

# INTRODUCTION

### PRELIMINARY RESULTS

The aim of this study is to assess, whether estimation of the same innovation-adoption model at farm- and municipality-level results in an **ecological fallacy**, meaning that based on aggregated data, one would make inverse inferences about the driving forces influencing a process happening at the individual level (Openshaw 1984). The adoption of oil-pumpkin cultivation in Austria serves as an applied example for our analysis (see Niedermayr et al. (2016) for background information).



*Figure 1:* Example for correct (left) and incorrect (right) inference from aggregated data. ▲ all farms (observed); ■ direct marketing farms (not observed); ● non direct-marketing farms (not observed). Source: own elaboration, modified from Jargowsky (2005).

# **DATA AND METHOD**

Figure 2 shows the methodological approach of our analysis:



The **dependent variable** is the share of oil-pumpkin cultivated land. Our **independent variables** describe natural conditions, proximity of oil-pumpkin specific infrastructure, productionmarketing- and policy- related factors, social, temporal and spatial factors. The inclusion of **spatial lag variables** (average value of neighbouring observations) allows a more detailed distinction between **direct effects** (difference between intercepts of dashed lines in *Figure 1*) and **contextual effects** (slopes of dashed lines in *Figure 1*). While most signs of the significant variables in *Table 1* do not change when comparing municipality- and farm-level results, we also observe differences.

For instance, **direct marketing** is beneficial for oil-pumpkin cultivation from a theoretical point of view, but the municipalitylevel model shows a negative relationship. Probably, at the municipality level, the presence of direct marketing farms, which do not cultivate oil pumpkin, leads to a bias of the true relationship of interest.

Table 1: Regression results at Municipality- and farm level	Table	1: Regression	results at	Municipality	- and farm	level
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Partial effect at the average (PEA)	Municip-	Farm
of independent Variables	ality level	level
Soil-quality index	0,04	0,01 ***
Distance to nearest drying facility	-0,20 ***	-0,10 ***
Livestock density	-0,11 *	-0,01 **
Log(farm size)	-0,01 *	-0,003 **
Log(UBAG subsidy for arable land)	-0,00	0,00
Log(arable land)	0,01	0,01 ***
Temporal lag of oil-pumpkin share	1,00 ***	0,09 ***
Direct marketing	-0,06 *	0,15 *
Organic farming	0,09 ***	0,95 ***
Agricultural education	0,03 **	0,08 *
WX of Direct marketing	-0,05	-0,00
WX of Organic farming	0,00	0,01 **
WX of Agricultural education	-0,01	0,003 *

Note: "Direct marketing", "Organic farming" and "Agricultural education" are dummies at the farm level and shares of farms at the municipality level; spatial-lag variables are denoted by the prefix "WX of"; \*\*\*, \*\* and \* and denote significance at the 1%, 5% and 10% level. Source: own elaboration, data from BMLFUW (2016).

### OUTLOOK

Potential ecological fallacies as outlined above could also be present in comparable studies, suggesting more **analyses at the farm-level**. However, the scarce availability of spatially explicit farm-level data is not likely to change in the near future. We therefore propose similarly to Schmidtner et al. (2015) further research on the topic, which could include **Monte Carlo simulations** in order to analyse the sensitivity of results with respect to the degree of aggregation of the underlying data.

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