Universität für Bodenkultur Wien

Spatial econometric and discrete choice models in agricultural economics: applications from Austria

Doctoral thesis submitted
in partial fulfilment of the requirements for the degree

Doctor rerum socialium oeconomicarumque (Dr.rer.soc.oec.)
at the University of Natural Resources and Life Sciences, Vienna; Institute of Agricultural and Forestry Economics

by

Andreas Niedermayr

Supervisor:

Univ.-Prof. Dr. Jochen Kantelhardt
University of Natural Resources and Life Sciences, Vienna; Institute of Agricultural and Forestry Economics

Advisors:

Ao.Univ.Prof. DI Dr. Stefan Vogel
University of Natural Resources and Life Sciences, Vienna, Institute for Sustainable Economic Development

Dr. Martin Kapfer
Bavarian State Research Center for Agriculture

Dr. Ulrich Morawetz
University of Natural Resources and Life Sciences, Vienna, Institute for Sustainable Economic Development

Location and date of submission: Vienna, 04 September 2018

Acknowledgements

I hereby want to thank everyone, who supported me during my dissertation and my time as a student at BOKU.

First of all, I would like to express my deep gratitude to my supervisor Univ.-Prof. Dr. Jochen Kantelhardt for the countless discussions, his valuable ideas, counsel and enthusiastic encouragement. Furthermore, I want to thank him for granting me the freedom to pursue my doctorate in the way I saw fit and for providing possibilities for me to attend international conferences, PhD-classes outside of BOKU and Austria, as well as international scientific exchange. Without his support, this dissertation would not have been possible.

A special thanks goes to my advisory team Ao.Univ.Prof. DI Dr. Stefan Vogel, Dr. Martin Kapfer and Dr. Ulrich Morawetz. They were always available, when I had questions. I would also like to thank Priv.-Doz. DI Dr. Franz Sinabell and Prof. Davide Viaggi for taking the time to assess my dissertation.

I am particularly grateful to my co-authors Dr. Pia Kieninger, Prof. Dr. Petr Mariel and Dr. Lena Schaller for their support. To Lena and Pia, I want to say thank you for the possibility to work with them on the PROVIDE-project, which opened a completely new field of research for me. To Petr I want to say thank you for introducing me to the 'mountain climbing' in discrete choice modelling and for providing me the possibility of a research visit in Bilbao.

Furthermore, I would like to thank all the people, I had the pleasure to get to know at AFO and INWE for their support and company throughout the last couple of years. My special thanks goes to my office colleague DI Peter Walder, my soccer colleagues Dr. Stefan Kirchweger and Ass. Prof. Dr. Michael Eder, and my other colleagues Michaela Grötzer, Manuela Packert, Kerstin Hafenscher, Anna Hinterseer, DI Ludwig Gerner, DI Fritz Wittmann and Heidi Leonhardt.

Finally, I want to thank my family and friends, first of all my parents Maria and Josef for making it possible for me to pursue an academic career, as well as my brother Stefan and his wife Waltraud for their support and the many discussions on agriculture. Babsi, without you I would not be, where I am today. You always were there for me when I had difficult times and encouraged me to go this way. Thank you.

Vienna, 04 September 2018 Andreas Niedermayr

Declaration of authorship

I hereby declare that I am the sole author of this work; no assistance other than that permitted has been used and all quotes and concepts taken from unpublished sources, published literature or the internet in wording or in basic content have been identified by footnotes or with precise source citations.

Vienna, 04 September 2018 Andreas Niedermayr

Abstract

This dissertation addresses two topics in agricultural economics that are of high relevance for agricultural policy: (i) the specialisation of farmers on a niche product with a focus on product origin as well as quality and (ii) multifunctional agriculture, which takes non-market outputs of farms stronger into account. In this thematic context, the broader aim of the thesis is to discuss the applicability of spatial econometric models and discrete choice models based on discrete choice experiments (DCEs) and possibilities to analyse different sources of heterogeneous outcomes with both methods in the context of two case-studies. Niedermayr et al. (2016) analyse spatial variations in the adoption of an emerging alternative crop with spatial econometric models in order to better understand the drivers, influencing the focus on a niche product with an emphasis on product origin and quality. They identify crop-specific factors, region-specific factors and spatial interdependence as drivers of adoption. Niedermayr et al. (2018) analyse the heterogeneous demand for an increased provision of environmental public goods (PGs) as one aspect of multifunctional agriculture with choice models based on a DCE. Their findings indicate a positive marginal willingness to pay for all three PGs analysed: groundwater quality, landscape quality and soil functionality in connection with climate stability. While in general, the exact identification of the sources of heterogeneous outcomes remains challenging, the results of the two case-studies show that incorporating comprehensive case-specific knowledge into the research process helps to adapt both methodologies in order to better reflect the case-specific processes, narrow down the possible sources of heterogeneity and thus generate results which are of immediate practical relevance.

Kurzfassung

Die vorliegende Dissertation befasst sich mit zwei agrarökonomischen Themen von großer Relevanz für die Agrarpolitik: (i) Der Spezialisierung von landwirtschaftlichen Betrieben auf Nischenprodukte und (ii) Multifunktionaler Landwirtschaft. In diesem thematischen Kontext ist das Ziel der Dissertation die Diskussion der Anwendbarkeit von räumlich ökonometrischen Modellen sowie Choice Modellen, basierend auf Diskreten Choice Experimenten (DCEs) sowie der Analyse unterschiedlicher Ursachen von heterogenen Modellergebnissen mittels zwei Fallstudien. Niedermayr et al. (2016) analysieren räumliche Variationen im Anbau einer alternativen Ackerkultur mit räumlich ökonometrischen Modellen, um ein besseres Verständnis bezüglich der Bestimmungsfaktoren zu erlangen, die eine Spezialisierung auf ein Nischenprodukt beeinflussen. Die identifizierten Bestimmungsfaktoren lassen sich in ackerkulturspezifische Faktoren, regionsspezifische Faktoren sowie räumliche Abhängigkeit unterteilen. Niedermayr et al. (2018) analysieren räumlich heterogene Präferenzen für eine erhöhte Bereitstellung öffentlicher Umweltgüter durch die Landwirtschaft, als einen Aspekt Multifunktionaler Landwirtschaft und ziehen hierfür Choice Modelle basierend auf DCEs heran. Die Ergebnisse deuten auf eine positive marginale Zahlungsbereitschaft für alle drei untersuchten öffentlichen Güter hin: Grundwasserqualität, Landschaftsqualität sowie Bodenfunktionalität in Verbindung mit Klimastabilität. Während generell eine exakte Identifikation der Ursachen für räumlich heterogene Ergebnisse in den Modellen schwierig bleibt, zeigen die Ergebnisse der Fallstudien, dass die Miteinbeziehung von umfangreichem fallspezifischen Wissen in den Forschungsprozess dabei hilft, die Methoden derart anzupassen, dass sie die fallspezifischen Vorgänge besser beschreiben, die möglichen Ursachen von Heterogenität einengen und somit zu praktisch relevanten Ergebnissen führen.

Table of contents

List of figures

List of tables

Abbreviations

ADI	Average Direct Impact
AIC	Akaike Information Criterion
AII	Average Indirect Impact
ASC	Alternative-Specific Constant
ATI	Average Total Impact
CAP	Common Agricultural Policy
CL	Conditional Logit
CSR	Case Study Region
CV	Contingent Valuation
DCE	Discrete Choice Experiment
ESS	Ecosystem Services
EU	European Union
GEV	Generalised Extreme Value
GMNL	Generalised Multinomial Logit
GNS	General Nesting Spatial
IACS	Integrated Administration and Control System
LCM	Latent Class Model
LULUCF	Land Use, Land Use Change and Forestry
MCMC	Markov Chain Monte Carlo
MIS	Multiple Indicator Solution

ML	Maximum Likelihood
MWTP	Marginal Willingness To Pay
MXL	Mixed Logit
OLS	Ordinary Least Squares
PDO	Protected Designation of Origin
PEA	Partial Effect at the Average
PGI	Protected Geographical Indication
PG	Public Good
RP	Revealed Preferences
RPL	Random Parameters Logit
RUM	Random Utility Model
SAC	Spatial Autoregressive Combined
SAR	Spatial Autoregressive
SDEM	Spatial Durbin Error Model
SDM	Spatial Durbin Model
SEM	Spatial Error Model
SLX	Spatial Lag of X
SP	Stated Preferences
UAA	Utilised Agricultural Area
WTA	Willingness To Accept

1 Research context

1.1 Introduction

Agriculture in the European Union (EU) faces increasing challenges both from markets and society. Agricultural markets have become more open and global, which has led to increasing competition between farms on the world market. At the same time, agriculture is subject to rising societal expectations with respect to product origin as well as quality and environmental impacts of farming (European Commission, 2017).

These challenges have led to different developments on farms, such as farm growth and (sustainable) intensification of agricultural production (Bartolini and Viaggi, 2013; Läpple et al., 2017; Wuepper et al., 2018), a focus on niche markets with an emphasis on product origin and quality (Albuquerque et al., 2018), a shift towards multifunctional agriculture, which takes non-market outputs stronger into account (Zasada, 2011), or an exit from the farming sector (Van der Ploeg et al., 2016). For policy makers it is essential to better understand these developments as well as the societal concerns associated with them in order to design effective, evidence-based policies that help to achieve policy aims in an efficient manner.

In this dissertation, two of these developments are analysed with econometric models. The covered topics are (i) spatial variations in the adoption of an emerging alternative crop as an example for the focus on a niche product with an emphasis on product origin as well as quality and (ii) the potential for an increased provision of environmental public goods (PGs) as one aspect of multifunctional agriculture. The analysis of both topics is associated with particular methodological challenges.

The adoption of a new product or production system may not only be influenced by the properties (e.g. complexity) of the product/production system (Useche et al., 2009) or the characteristics of the farmers (Knowler and Bradshaw, 2007) who are considered as potential adopters, but also by spatial effects. For example, spatially heterogeneous agroclimatic preconditions may explain spatial patterns of adoption rates (Feder and Umali, 1993) or the effect of determinants on adoption may also vary throughout space. This phenomenon is referred to as spatial heterogeneity in the literature (Anselin, 2010)[1]. Alternatively, if observed values at one location depend on observed values at neighbouring locations (and vice versa), this is referred to as spatial (inter)dependence, which is associated with spatial interaction effects in spatial econometrics (LeSage and Pace, 2009; Elhorst, 2014; Storm et al., 2015). With respect to the adoption of a new crop, spatial interaction effects could for example arise through social learning among peers (Conley and Udry, 2010) or a shared use of resources (Garrett et al., 2013). The implementation of these aspects in an empirical analysis is possible with spatial econometric methods (LeSage and Pace, 2009). However, one problem in this context, which has received less attention in the empirical literature, is the difficulty of differentiating between the multiple channels through which spatial effects may arise (Gibbons and Overman, 2012).

Regarding the potential for an increased provision of PGs by agriculture, the fundamental problem is that there exists no market for PGs, as they are defined by the criteria of non-rivalry and non-excludability (Samuelson, 1954). Consequently, there is a need to examine whether society has a demand for an increased provision of public goods by the agricultural sector. The demand for public goods can be evaluated with revealed or stated preference methods. While revealed preference methods try to elicit the preferences of people by finding a link between the public good of interest and observed behaviour of people on markets (Blow and Blundell, 2018), stated preference methods create hypothetical settings in which respondents can directly state their preferences for the public good of interest (Louviere and Hensher, 1982).

Discrete choice experiments (DCEs) belong to the stated preference methods, and represent the most prominent valuation method in this context. In a DCE, respondents state their preferences for PGs by choosing between two or more multi-attribute alternatives (Johnston et al., 2017). Based on the data from DCEs, discrete choice models are applied to estimate preferences and marginal willingness to pay (MWTP) for an improved provision of environmental public goods (Adamowicz et al., 1998b). While DCEs are well-linked to consumer-demand theory (Lancaster, 1966), their results are highly case-sensitive due to the hypothetical nature of the choice experiment and unobserved heterogeneity affecting choices (Louviere, 2006; Hensher, 2010). A current methodological issue in this context evolves around two channels through which such unobserved heterogeneity may arise: heterogeneity of estimated preference-weights

[1] The term spatial heterogeneity is used to describe variables (for example agroclimatic conditions) or functional relationships between variables (for example the effect of agroclimatic concicitions on the adoption of a crop) that differ in space Anselin (1988).

(i.e. preference heterogeneity) or heterogeneity associated with other unobserved factors among respondents (i.e. scale heterogeneity) (Hensher et al., 2015; Hess and Train, 2017).

In the above described thematic context, the broader aim of the thesis is to discuss the applicability of spatial econometric models and discrete choice models based on DCEs and possibilities to analyse the above described sources of heterogeneous outcomes with both methods by taking recent methodological developments into account.

Two papers are implemented in the thesis. The first paper (Niedermayr et al., 2016) analyses spatial variations in the cultivation of an emerging alternative crop, considering the crop-specific context, the region-specific context and spatial interdependence. The second paper (Niedermayr et al., 2018) takes a consumer-demand point of view and analyses heterogeneous preferences for public goods provided by agriculture in a region of intensive agricultural production. Both analyses take on a local perspective and focus on a particular case study. With this approach it is possible to adapt both methodologies in order to better reflect the case-specific processes, and thus generate results which are of immediate practical relevance.

The further structure of this introductory chapter is as follows: the next section describes the methodological background regarding spatial econometrics and discrete choice modelling based on data from DCEs. The third section summarises the two papers as well as their policy relevance and discusses their contribution to the respective literature. The fourth section summarises the findings and limitations of the thesis before providing concluding remarks and avenues for future research. After this introductory chapter, the remaining chapters of the present dissertation contain the full texts of the two published papers and an appendix, which summarises additional research and teaching activities auf the author

1.2 Methodological background

This section gives an overview of spatial econometric and discrete choice models. Both methods are increasingly applied in the agricultural economic literature.

The rise of spatial econometric applications is attributable to recent advances in computing power in combination with a rising availability of spatial data and a growing interest in the spatial perspective of economic processes (see for example Anselin (2010) for an overview of these developments). Additionally, the close link of agricultural production to space, due to the immovability of the production factor land, makes questions regarding spatial effects particularly relevant for research in agricultural economics (Lippert, 2006; Viaggi et al., 2013; Storm et al., 2015; Feichtinger and Salhofer, 2016).

Discrete choice models based on DCEs are increasingly applied to analyse preferences of individuals with respect to non-market goods and services connected to agriculture (Adamowicz et al., 1994; Kallas et al., 2007; Hoyos, 2010; Zasada, 2011; van Zanten et al., 2014). Their key advantage compared to revealed preference methods is that they can be easily used in cases, where it is difficult to establish a connection between a public good and the behaviour of people on markets (Adamowicz et al., 1998a). This is especially relevant for agriculture, as due to its multifunctional nature (Randall, 2002) it provides many non-market outputs. The enhanced provision of these non-market outputs has become a focus of the common agricultural policy (CAP) of the EU in recent years (European Commission, 2017).

1.2.1 Spatial econometrics

The term spatial econometrics can be traced back to the work of Paelinck and Klaassen (1979). A formal representation of different spatial econometric models was established by Anselin (1988). The application of spatial econometric models has also been supported by the rise of the New Economic Geography (Krugman, 1991), which was marked by an increasing interest in measuring spatial externalities in an economic setting. In principle, spatial econometric models expand non-spatial regression models by including spatial relations between observations in a regression model, which allows one to analyse spatial phenomena in economics such as externalities, interactions or spatial concentration (LeSage and Pace, 2009).

The starting point is a basic linear ordinary least squares model, which is defined as

$$\mathbf{Y} = \alpha\boldsymbol{\iota}_{\mathbf{N}} + \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\varepsilon}, \tag{1}$$

where $\mathbf{Y}$ is a $\mathbf{N} \times \mathbf{1}$ representing the dependent variable and $\mathbf{N}$ represents the number of observations $(\mathbf{i} = \mathbf{1}, \dots, \mathbf{N})$, $\boldsymbol{\alpha}$, is a constant parameter, $\boldsymbol{\iota}_{\boldsymbol{N}}$ is a $\mathbf{N} \times \mathbf{1}$ vector of ones, $\mathbf{X}$ denotes a $\mathbf{N} \times \mathbf{K}$ matrix of independent variables, $\boldsymbol{\beta}$ is a vector of $\mathbf{K}$ parameters to be estimated and $\boldsymbol{\varepsilon}$ is a $\mathbf{N} \times \mathbf{1}$ vector, representing a stochastic error term, which is assumed to be independently and identically distributed for all observations with a mean of $\mathbf{0}$ and variance $\boldsymbol{\sigma}^{\mathbf{2}}$ (Elhorst, 2014).

The spatial relations (i.e. neighbourhood) between observations in spatial econometric models are expressed with a spatial weights matrix $\mathbf{W}$**,** with the dimensions $\mathbf{N} \times \mathbf{N}$, which contains for each observation information regarding its (spatial)[2] connection to other observations. In its simplest form such a matrix differentiates between the value $\mathbf{1}$ if two observations are neighbours and the value $\mathbf{0}$ if they are not neighbours. Neighbourhood can be defined in many different ways, for example based on shared borders of regions or a cut-off distance between observations (Getis, 2009). Therefore, the researcher has to decide on the definition of neighbourhood on a case by case basis, guided by economic theory and/or specific knowledge of the research topic (Corrado and Fingleton, 2012; Storm and Heckelei, 2018). An example of a spatial weights matrix is provided in (2)

$$\mathbf{W} = \begin{array}{cccc} & \mathbf{A} & \mathbf{B} & \mathbf{C} \\ \mathbf{A} & \mathbf{0} & \mathbf{1} & \mathbf{0} \\ \mathbf{B} & \mathbf{1} & \mathbf{0} & \mathbf{1} \\ \mathbf{C} & \mathbf{0} & \mathbf{1} & \mathbf{0} \end{array}, \tag{2}$$

which describes the spatial relations between three observations $(\mathbf{A}, \mathbf{B}, \mathbf{C})$. In this example it is assumed that these observations are administrative regions like municipalities and neighbourhood between them is defined based on shared borders. According to the spatial weights matrix, $\mathbf{A}$ is a neighbour of $\mathbf{B}$, $\mathbf{B}$ is therefore also a neighbour of $\mathbf{A}$, but also a neighbour of $\mathbf{C}$ and $\mathbf{C}$ is a neighbour of $\mathbf{B}$. One key characteristic of a spatial weights matrix is that it has a diagonal of zeroes, as an observation is usually not considered to be a neighbour of itself (LeSage and Pace, 2009). When used in spatial econometric models, the spatial weights matrices are mostly row-standardised, so that each row sums up to unity

$$\mathbf{W} = \begin{matrix} \mathbf{0} & \mathbf{1} & \mathbf{0} \\ \mathbf{0,5} & \mathbf{0} & \mathbf{0,5} \\ \mathbf{0} & \mathbf{1} & \mathbf{0} \end{matrix}. \tag{3}$$

If a matrix product between the spatial weights matrix $\mathbf{W}$ and a variable $\mathbf{Z}$ is calculated, the result is a weighted value of the neighbouring observations of $\mathbf{Z}$, also referred to as a spatial lag variable $\mathbf{WZ}$ (Anselin, 1988). An example of this calculation is given in equation (4).

$$\mathbf{WZ} = \begin{pmatrix} \mathbf{0} & \mathbf{1} & \mathbf{0} \\ \mathbf{0,5} & \mathbf{0} & \mathbf{0,5} \\ \mathbf{0} & \mathbf{1} & \mathbf{0} \end{pmatrix} \begin{pmatrix} \mathbf{z_A} \\ \mathbf{z_B} \\ \mathbf{z_C} \end{pmatrix} = \begin{matrix} \mathbf{z_A} \times \mathbf{0} + \mathbf{z_B} \times \mathbf{1} + \mathbf{z_C} \times \mathbf{0} \\ \mathbf{z_A} \times \mathbf{0.5} + \mathbf{z_B} \times \mathbf{0} + \mathbf{z_C} \times \mathbf{0.5} \\ \mathbf{z_A} \times \mathbf{0} + \mathbf{z_B} \times \mathbf{1} + \mathbf{z_C} \times \mathbf{0} \end{matrix} = \begin{matrix} \mathbf{y_B} \\ (\mathbf{z_a} + \mathbf{z_c})/\mathbf{2} \\ \mathbf{y_B} \end{matrix} \tag{4}$$

[2] While a spatial weights matrix usually only refers to a spatial context, similar concepts are also applied to model interaction effects in a non-spatial context like for example social networks Conley and Udry (2010), or economic connections Corrado and Fingleton (2012).

In such a simple case the weights are formulated so that each neighbour contributes equally to the resulting spatial lag variable (i.e. the result is an average). However, the spatial weights may also be defined differently (Getis, 2009). For example the contribution of each neighbour is often weighted by the inverse of its distance, which leads to a diminishing contribution of observations with increasing distance (LeSage and Pace, 2009). According to LeSage (2014), the definition of neighbourhood and spatial weights in a spatial weights matrix should primarily be based on information regarding the research context.

Different spatial lags can be added to the OLS model in equation (1), leading to various spatial econometric models with a total of three possible kinds of spatial interaction effects. An overview of the resulting cross-sectional spatial econometric models and their interrelations is given in Figure 1[3].

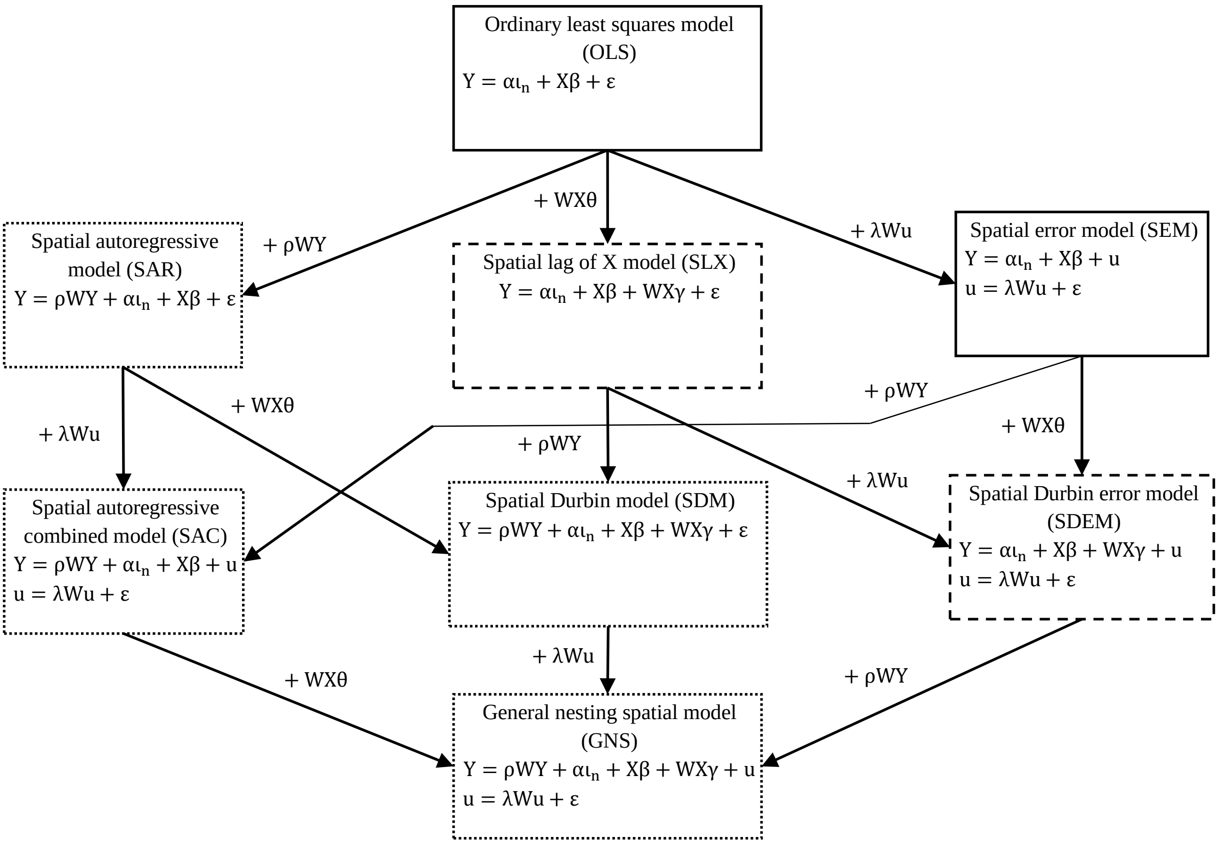

Figure 1. Overview of spatial econometric models

Source: own representation, adapted from Halleck-Vega and Elhorst (2015). *Note: dotted lines represent models with global spillover effects, dashed lines represent models with local spillover effects and solid lines represent models with no spillover effects.*

[3] For a more comprehensive description of cross-sectional spatial econometric models, but also static and dynamic spatial panel models, the interested reader may refer to Elhorst (2014).

Adding spatial lags of the dependent variable $\mathbf{WY}$ and estimating the associated parameter $\boldsymbol{\rho}$ leads to the spatial autoregressive (SAR) model[4] (Anselin, 1988). With this model, (i) endogenous interaction effects can be modelled, describing interactions between dependent variables. For example, the price for agricultural land may not only depend on its own characteristics but also on prices payed for nearby land. Another example, referring to the first paper implemented in this thesis (Niedermayr et al., 2016), is the decision whether to plant (adopt) a new crop. In such a case the farmers' decisions may be influenced by the behaviour of neighbouring farmers. One recent application of the SAR model is Schmidtner et al. (2012), who analyse the spatial distribution of organic farming in Germany.

Adding spatial lags of the error term $\mathbf{Wu}$ and estimating the associated parameter $\boldsymbol{\lambda}$ results in the spatial error model (SEM) (Anselin, 1988). This model captures (ii) interaction effects among the error terms by splitting the error term into two parts: one part follows the same spatial autoregressive process like the spatial lag of **Y** in the SAR model and the other part has the same properties like the error term of equation (1). Staying with the decision of a farmer to plant a new crop, these interaction effects can stem from unobserved factors like the presence of a farm advisor, which provides information to the farmers about the new crop, or from unobserved heterogeneity of agroclimatic conditions (i.e. the suitability of arable land for the new crop). For example, Gellrich and Zimmermann (2007) estimate a SAR model and a SEM in order to analyse spatial patterns of agricultural land abandonment in the Swiss alps.

Finally, adding spatial lags of the independent variables **WX** and estimating the associated parameter $\boldsymbol{\gamma}$ leads to the spatial lag of X (SLX) model (LeSage and Pace, 2009). With this model (iii) exogenous interaction effects can be estimated, describing the influence of independent variables of neighbouring observations on the dependent variable of a region. Examples could be a positive externality caused by a good regional marketing infrastructure for the new crop, as it is found in (Niedermayr et al., 2016) (2016), or the shared use of resources like special machinery.

The most general model, combining all three types of interaction effects, is labelled as general nesting spatial model (GNS) by Elhorst (2014) and Halleck-Vega and Elhorst (2015). By imposing certain restrictions on the parameters $\boldsymbol{\rho}$, $\boldsymbol{\lambda}$ and $\boldsymbol{\gamma}$, three further models can be derived. The spatial autoregressive combined (SAC) model (LeSage and Pace, 2009), where $\boldsymbol{\gamma} = \mathbf{0}$,

[4] The SAR model is also often denoted as spatial lag model in the literature.

combines endogenous interaction effects and interaction effects among the error term. The spatial Durbin model (SDM) (LeSage and Pace, 2009), where $\boldsymbol{\lambda} = \mathbf{0}$ includes endogenous as well as exogenous interaction effects. In the spatial Durbin error model (SDEM), (LeSage and Pace, 2009) $\boldsymbol{\rho} = \mathbf{0}$ and it therefore combines exogenous interaction effects and interaction effects among the error terms. Lastly, if all of the spatial parameters are zero, the equation reduces to that of the OLS model.

With respect to marginal effects of changes in the independent variables on the dependent variable within the different models, a differentiation is made between direct effects and indirect (spillover) effects. Spillover effects can be further divided into global and local spillover effects and are mostly of main interest in spatial econometric analyses (LeSage, 2014). It is important to be aware of the different interpretational meaning and magnitude of the two types of spillover effects. Global spillover effects do not only affect neighbouring observations but pass like a wave through all observations, affecting neighbours of neighbours and so on, ultimately leading to feedback loops to the initial observation (LeSage and Pace, 2009). In contrast, exogenous spillover effects only affect observations, that are connected through the spatial weights matrix $\mathbf{W}$ (Halleck-Vega and Elhorst, 2015). The models in Figure 1 which are framed by a dotted line (SAR, SAC, SDM and GNS) produce global spillover effects, while the ones with dashed lines (SLX and SDEM) create local spillover effects and models with solid lines have no spillover effects.

For the models with local spillover effects, the parameter vector $\boldsymbol{\beta}$ directly represents the direct effects and the parameter vector $\boldsymbol{\gamma}$ describes the spillover effects (provided that the spatial weights matrix is row-standardised). For models with global spillover effects, the calculation of direct and spillover effects is more complicated[5], because it involves a so-called spatial multiplier matrix $(\mathbf{I} - \boldsymbol{\rho}\mathbf{W})^{-1}$ (Anselin, 2003). In this matrix expression, $\mathbf{I}$ denotes an $\mathbf{N} \times \mathbf{N}$ identity matrix with diagonal elements of ones and off-diagonal elements of zeroes. Alternatively, the matrix can be described as

$$(\mathbf{I} - \boldsymbol{\rho}\mathbf{W})^{-1} = \mathbf{I} + \boldsymbol{\rho}\mathbf{W} + \boldsymbol{\rho}^{2}\mathbf{W}^{2} + \boldsymbol{\rho}^{3}\mathbf{W}^{3} \ldots \tag{5}$$

[5] For a description of how the direct and indirect effect of the spatial models mentioned in this text are derived, please refer to LeSage and Pace (2009) or Elhorst (2014). Moreover, Golgher and Voss (2016) provide a more detailed step by step explanation of the required calculations.

In this formula $\mathbf{W^2}$ identifies neighbours of second order (neighbours of neighbours), $\mathbf{W^3}$ neighbours of third order (neighbours of neighbours of neighbours) and so on. Due to the presence of such higher orders of $\mathbf{W}$, the above described feedback loops of global spillover effects arise (LeSage and Pace, 2009).

Originally, in many empirical applications, the parameter $\boldsymbol{\rho}$ of the SAR model was directly interpreted as a spillover effect and the parameter vector $\boldsymbol{\beta}$ as a direct effect (Elhorst, 2014). However, LeSage and Pace (2009) show that this is not true and derive marginal effects, involving the spatial multiplier matrix. In general, the marginal effects of such models take on the form of $\mathbf{K}$ matrices, one for each independent variable. Each matrix has the dimensions $\mathbf{N} \times \mathbf{N}$. These matrices differ slightly between the SAR/SAC $[(\mathbf{I}-\boldsymbol{\rho}\mathbf{W})^{-\mathbf{1}}\boldsymbol{\beta}_{\mathbf{k}}]$ and SDM/GNS $[(\mathbf{I}-\boldsymbol{\rho}\mathbf{W})^{-\mathbf{1}}(\boldsymbol{\beta}_{\mathbf{k}}+\mathbf{W}\boldsymbol{\gamma}_{\mathbf{k}})]$ models, as the last two also involve spatial lags of the independent variables. However, in both cases the direct and indirect effects are observation-specific (i.e. they differ for each observation in the dataset). LeSage and Pace (2009) therefore provide summary measures of these marginal effects, which they label average direct impact (ADI) and average indirect impact (AII). The ADI is represented by the column sum of the matrix and the AII is described by the row/column sum of the matrix. The sum of the two impact measures gives the average total impact (ATI).

Which of the above described models (and consequently also which spillover effect or no spillover effect) to implement in an empirical application is not straight forward. Statistical procedures which can be used to compare competing model specification based on their fit to the data are Lagrange multiplier tests (Anselin et al., 1996) or Bayesian model comparison techniques (LeSage and Pace, 2009; Lacombe et al., 2014). However, the different spatial econometric models are based on different theoretical motivations and thus a different interpretational meaning. Therefore, it is difficult to properly differentiate between competing model specifications only based on their fit to the data (Gellrich and Zimmermann, 2007).

One important limitation of the SAR and SAC models, that has been pointed out recently is that the sign of direct and indirect effects is the same for all independent variables, and additionally the ratio of the two effects is constant for all variables. This is a very restrictive property and very unlikely in empirical applications (Elhorst, 2010; Pace and Zhu, 2012).

Furthermore, the more complex models, involving more than one spatial lag variable, suffer from identification issues regarding the parameter estimates of the spatial lag variables. This is particularly the case for the GNS model and to a lesser extent also the SAC model, the SDM and SDEM (Elhorst, 2014). Especially in the GNS and SAC models, the two parameters $\boldsymbol{\rho}$ and

λ have the tendency to become unstable and interchange their magnitudes (Elhorst, 2014). A similar problem occurs if one compares SDM and SDEM estimates, where it also becomes difficult to decide between the competing specifications solely based on statistical tests, because of their different interpretational meaning.

Models involving endogenous interaction effects and/or interaction effects of the error term also require special estimation procedures, as the inclusion of a spatial autoregressive process in the dependent variable induces endogeneity and in the error term leads to unbiased, but inefficient estimates (Anselin, 1988; Elhorst, 2014). Available estimation procedures are for example maximum likelihood (ML) (Ord, 1975) or Bayesian Markov chain Monte Carlo (MCMC) estimation (LeSage, 1997). Models with exogenous interaction effects do not have these drawbacks and can therefore be estimated with simpler estimation methods like ordinary least squares (OLS), provided that the dependent variable is continuous (Halleck-Vega and Elhorst, 2015). For limited dependent variables, Probit, Logit or Tobit models are more adequate and can also be extended to the above described spatial models (LeSage and Pace, 2009).

1.2.2 Discrete choice models based on data from discrete choice experiments

Originating from the field of transport economics (Louviere and Hensher, 1982), DCEs and the econometric analysis of their results with discrete choice models are also common in marketing (Louviere and Woodworth, 1983), health economics (Clark et al., 2014), environmental economics (Hoyos, 2010) or the partly overlapping field of agricultural economics (Randall, 2002). In agricultural economics, they have been increasingly applied to valuate non-market outputs of agriculture with public good characteristics (Ragkos and Theodoridis, 2016). Other, again partly overlapping topics are for example farmers' preferences for participation in agri-environmental schemes (Espinosa-Goded et al., 2010), consumer preferences for organic labels (Zanoli et al., 2013), geographical indications (Aprile et al., 2012) or animal welfare (Carlsson et al., 2007).

DCEs build on the consumer demand theory of Lancaster (1966), who emphasises that consumers do not derive utility from goods and services themselves, but from their characteristics (attributes), which can take on different levels. In a DCE, choice data is generated through the construction of a hypothetical market by using a survey, where respondents are presented with several choice sets, each consisting of at least two alternatives, which are marked by a set of attributes with varying outcomes (i.e. levels) (Hoyos, 2010). By choosing their preferred alternative in each choice set, they make trade-offs between the levels of the attributes of the respective alternatives in each choice set (Hoyos, 2010), from which their preferences for the good/service of interest can be derived. In the context of environmental economics or agricultural economics, choice sets also typically include a fixed status-quo alternative, which describes the current levels of the public goods of interest (Meyerhoff and Liebe, 2009).

A choice set example for the valuation of public goods provided by agriculture in the Marchfeld region in Austria is provided in Table 1. This choice card consists of three alternatives, each with four attributes. One of the alternatives describes the current status quo and the other two (A and B) show hypothetical attribute level combinations. Three of the attributes describe a public good (appearance of the agricultural landscape, groundwater quality and carbon sequestration through conservation agriculture), while the fourth is a cost attribute, describing additional costs for respondents, associated with the respective alternative.

Table 1. Example of a choice card

	Alternative A	Alternative B	Status Quo
Percentage of flower strips and hedges on agricultural area	 10%	 2.5%	 2.5%
Groundwater potable	only after treatment	without treatment	only after treatment
Saved annual GHG emissions	20,000 households	30,000 households	No GHG-emissions saved
Additional costs	80 €	120 €	0 €
I would choose	□ Alternative A	□ Alternative B	□ Status Quo

Source: Niedermayr et al. (2018)

Experimental designs are used to generate attribute level combinations in the choice sets, aimed at estimating unconfounded parameters, describing the preferences of respondents with econometric models (Hoyos, 2010). Basically, they define which attribute level combinations will appear in the choice experiment. From a theoretical point of view, full factorial designs, consisting of all possible attribute level combinations, are the most desirable option as they allow to estimate all types of effects of the attributes on utility, including non-linear effects and all possible interaction effects between attributes (ChoiceMetrics, 2014). However, in practice such designs are not feasible due to the high number of possible combinations. For example, in a relatively simple case with two alternatives, each with 3 attributes with 4 levels, the total number of combinations is equal to 4,096 (ChoiceMetrics, 2014). In such a setting, the necessary number of respondents and/or the number of choice set per respondent would obviously be not feasible.

Therefore, designs with a reduced number of combinations (fraction) are normally used. Such designs may for example be defined on the basis of orthogonality (so-called orthogonal designs), translating into attribute-level balance and no correlation between attributes (Hensher et al., 2015), or on measures, aimed at optimizing the statistical efficiency (so-called efficient designs) (Kuhfeld et al., 1994). For the latter type of designs it is necessary to acquire prior information about the parameters one wishes to estimate, which is normally done through pilot studies or in some cases through information from previous studies (ChoiceMetrics, 2014). While efficient designs have gained increasing popularity, because in theory they would allow for a smaller minimum sample size, they have recently also been criticised for their lack of robustness, if the priors are wrong (Walker et al., 2018). In order to further reduce the number of choice sets per respondent and thus the cognitive burden, the designs can additionally be split into several blocks, each representing a subset of the original design (Hensher et al., 2015). A block is not fully orthogonal by itself (only the whole design is), but attribute-level balance is sustained within each block (ChoiceMetrics, 2014).

In general, the survey development is a very sensitive process and should always be aimed at maximizing the validity (minimization of bias) and reliability (minimization of variability) of the preference estimates (Johnston et al., 2017). The researcher needs to decide for example on the definition of the target population of the survey, the description of the attributes as well as their levels (number of levels, unit of measurement, range), the status-quo alternative or additional information provided to respondents. Therefore, this process requires a comprehensive understanding of the domain under investigation and of how possible respondents perceive the presented information. Thus, extensive qualitative pretesting, involving members of the target population and other stakeholders which are relevant in the research context is essential for this purpose (Johnston et al., 2017)[6].

[6] For more detailed information on the development and implementation of discrete choice experiments, the interested reader is referred to Hoyos (2010) or Johnston et al. (2017).

Once the data from the discrete choice experiment has been acquired, it can be analysed with choice models based on the random utility framework (McFadden, 1974)[7]. Such random utility models (RUM) explain utility $\mathbf{U}_{nj}$ of an individual $\mathbf{n}$ for an alternative $\mathbf{j}$ by decomposing it into an observable $(\mathbf{V_{nj}})$ and unobservable $(\boldsymbol{\varepsilon}_{\mathbf{nj}})$ part and assuming that these two parts can be added up to get the total utility $\mathbf{U_{nj}}$. The observable part of utility is assumed to be the weighted sum of attributes $\mathbf{x_{nj}}$, where the weights for the attributes $\boldsymbol{\beta}$ express the magnitude of the preferences for the respective attribute. The idea is to estimate weights $\boldsymbol{\beta}$ that maximise the probability of the observed choices made by respondents. Estimation is mostly carried out with the (simulated) maximum likelihood method (Train, 2009), but alternative estimation procedures, for example based on Bayesian statistics (Albert and Chib, 1993), are also available. The basic assumptions of these models are that people choose a good among a finite number of mutually exclusive alternatives in order to maximise their utility, given a limited budget (Ryan et al., 2008). Different assumptions regarding the distribution of the unobserved part of utility $\boldsymbol{\varepsilon}_{\mathbf{nj}}$ lead to different econometric models[8]. Train (2009) differentiates between logit, generalised extreme value (GEV), mixed logit (MXL) and Probit models.

The conditional logit (CL) model, which is also often referred to as multinomial logit (MNL) model is the most basic RUM (McFadden, 1974). The utility in this model is defined as

$$\mathbf{U_{nj}} = \boldsymbol{\beta}\mathbf{x_{nj}} + \boldsymbol{\varepsilon}_{\mathbf{nj}} \tag{6}$$

and the error term is assumed to be identically and independently (iid) extreme value type 1 distributed, which is also referred to as Gumbel-distribution.

The choice probability of the CL model is defined as

$$\mathbf{P_{nj}} = \frac{\mathbf{e}^{\boldsymbol{\beta}\mathbf{x_{nj}}}}{\sum_{\mathbf{k=1}}^{\mathbf{K}} \mathbf{e}^{\boldsymbol{\beta}\mathbf{x_{nk}}}}, \tag{7}$$

where $\mathbf{e}$ denotes the exponential function and $\mathbf{k}$ is an indicator for other alternatives than $\mathbf{j}$.

Three important underlying assumptions of this model are that (i) preferences are homogeneous among respondents, (ii) the unobserved part of utility is uncorrelated over alternatives and has

---

[7] It is important to note that random utility models can also be applied to data stemming from revealed preference methods.

[8] For a more detailed description of models, the interested reader is referred to Train (2009) or Hensher et al. (2015) and to Hess and Train (2017) for a recent guide regarding model choice.

the same variance over all alternatives and (iii) the unobserved part of utility is uncorrelated over time, when a series of choices is observed by one individual (Train, 2009). These assumptions are rather restrictive. For example, one would intuitively expect that the unobserved factors which affect one choice of an individual, would be similar to those affecting other choices of the same individual, translating into correlation among the errors across a series of choices (Train, 2009). However, these assumptions also lead to a relatively simple choice probability, which is globally concave and is therefore easy to estimated (Hensher et al., 2015).

Several alternative models have been developed, which relax some or all of these assumptions of the CL model and have gained in popularity with the increase of computational power in recent decades (Hoyos, 2010). However, the CL model is still a very useful basic specification to check for the robustness of more complex econometric models (Johnston et al., 2017).

GEV models relax the assumption of no correlation and constant (homogeneous) variance of unobserved factors (Train, 2009). The idea behind these models is that some of the alternatives are more similar to one another than to others (Train, 2009). This is for example often relevant in DCEs with labelled alternatives (i.e. alternatives with names, which communicate information about them) (Hensher et al., 2015). Labelled alternatives are for example often used for an analysis of peoples' preferences for travelling to work (Arentze et al., 2003). An example would be a setting, where respondents choose between four different alternatives, considering for example travel time, comfort and cost as attributes and the alternatives additionally labelled as own car, taxi, bus and train. In such an example, the unobserved factors affecting the choices of own car and taxi (car) on the one hand and bus and train (public transport) on the other hand could be correlated. Such a setting could be described with a nested Logit model (Williams, 1977), where the similar alternatives are grouped into nests. Similarly, if it is assumed that the variance of the unobserved factors differs over alternatives, this would lead to a heteroscedastic logit model (Bhat, 1995).

Probit models relax all three of the above described assumptions of the CL model and thus allow for heterogeneous preferences of respondents as well as correlation and heteroscedasticity (heterogeneous variance of the unobserved factors) in any form (Hoyos, 2010). One restriction of the Probit models is that they assume a joint normal distribution of the unobserved factors which potentially leads to unrealistic results when heterogeneous preferences of respondents are modelled (Train, 2009). This distributional assumption would imply that some respondents in a DCE including a price attribute would have positive preferences for an increase in price, as the density of the normal distribution stretches from minus infinity to plus infinity (Train, 2009). Also, compared to the CL and GEV models, estimation of a Probit model is computationally much more demanding (Hoyos, 2010), which is why it is hardly used in empirical studies.

MXL models are by far the most widely used RUM in the context of the econometric analysis of DCEs (Train, 2009). They allow to relax all three above described assumptions of the CL model by decomposing the unobserved factors into two parts: one part, which contains all the correlation and heteroscedasticity and for which any distribution can be specified and a second part, which is assumed to be iid extreme value type 1 distributed (Train, 2009). MXL models are therefore considered as the most flexible discrete choice models, that can approximate any other discrete choice model (McFadden and Train, 2000). A general description of the choice probability of a MXL model is given as

$$\mathbf{P_{nj}} = \int \mathbf{L_{nj}}(\boldsymbol{\beta})\, \mathbf{f}(\boldsymbol{\beta})\mathbf{d}\boldsymbol{\beta}, \tag{8}$$

which is basically the integral of Logit probabilities over a density of parameters. In this equation $\mathbf{L_{nj}}$ is the Logit probability as defined in equation (7), evaluated at parameters $\boldsymbol{\beta}$, and $\mathbf{f}(\boldsymbol{\beta})$ is a density function, which has to be specified by the researcher and is referred to as a mixing distribution (hence the name mixed logit) (Train, 2009). If the mixing distribution is assumed to be discrete, where $\boldsymbol{\beta}$ takes on a finite number of $\mathbf{M}$ values, this leads to a so-called latent class model (LCM), where preference weights $\boldsymbol{\beta}$ are estimated for each of the $\mathbf{M}$ latent classes (Train, 2009). If the mixing distribution is assumed to be continuous, this leads to the random parameters logit (RPL) model[9], which also assumes that preferences of respondents are heterogeneous and vary with the density of $\boldsymbol{\beta}$ (Hensher et al., 2015). If the density of $\boldsymbol{\beta}$ is for example assumed to be a normal with mean $\mathbf{b}$ and covariance $\mathbf{W}$, the choice probability is defined as

$$\mathbf{P_{nj}} = \int \mathbf{L_{nj}}(\boldsymbol{\beta})\, \boldsymbol{\phi}(\boldsymbol{\beta}|\mathbf{b}, \mathbf{W})\mathbf{d}\boldsymbol{\beta}, \tag{9}$$

where $\mathbf{b}$ and $\mathbf{W}$ are the parameters to be estimated (Train, 2009). Instead of a point estimate of $\boldsymbol{\beta}$ like in the CL model, an RPL model therefore allows to estimate preference heterogeneity in form of a distribution of $\boldsymbol{\beta}$. Any other distribution may be chosen for the density of $\boldsymbol{\beta}$, for example log-normal, triangular or uniform (Hensher et al., 2015). Estimation of this model requires simulation-based estimation like the simulated maximum likelihood method, as the

[9] The terms mixed logit and random parameters logit are often used as synonyms, with many applications which estimate a RPL model referring to it as MXL model.

choice probability and the associated log-likelihood function have no closed-form solution (Train, 2009).

As utility is an abstract concept and its units are therefore unknown, two important aspect need to be considered, when estimating any RUM: only differences in utility matter and the scale of utility is arbitrary (Train, 2009). This means that there is no need to know the absolute level of utility of different alternatives, only their differences in utility matter. If any given constant is added to, or multiplied with each alternative, the alternative with the highest utility does not change. In order to estimate any RUM it is therefore necessary to normalise utility to some arbitrary scale (Hensher et al., 2015). In Logit models, this is done by setting the variance of the unobserved factors $\boldsymbol{\varepsilon}_{\mathbf{nj}}$, $\boldsymbol{\sigma}^{\mathbf{2}}$ to a pre-defined constant. In such a case the estimated parameters are not the $\boldsymbol{\beta}$, but their ratio with the standard deviation of the error term $\boldsymbol{\sigma}$ $(\boldsymbol{\beta}/\boldsymbol{\sigma})$, which is usually referred to as scale factor (Train, 2009). In models, where the variance of the error term is assumed to differ for different segments of the population (e.g. people from a city and from the countryside), the scale factor is set for one segment and is estimated for the other segments, relative to the first segment (Hensher et al., 2015). If errors are assumed to be correlated over alternatives/time, as for example in the Probit or MXL models, the normalization is more complicated and needs to consider the correlation structure of error terms (Train, 2009).

With the information regarding preferences of respondents expressed through the estimated parameters ($\boldsymbol{\beta}$ in the case of CL, $\mathbf{b}$ and $\mathbf{W}$ in a RPL model) marginal rates of substitution can be calculated to express how much of one attribute level respondents are willing to trade for a unit-increase in another attribute level (Hoyos, 2010). If one of the attributes in a DCE describes the price of the alternatives, this procedure can be used to calculate a MWTP, describing how much respondents are on average willing to pay for a unit increase in the level of one attribute (Hensher et al., 2015). In the CL model this is simply the negative ratio of the parameter of a non-price attribute and a price attribute. In a RPL model the procedure is similar. However, if both, the price and non-price attribute coefficients are random parameters, calculation of the MWTP requires simulation. Simulation can for example be carried out with the procedure developed by Krinsky and Robb (1986), where random draws are taken from both distributions, MWTP is calculated for each pair of draws, and mean, median and percentiles of the resulting simulated distribution of MWTP can be acquired.

1.3 Summary of the papers and their contribution to the literature

This section summarises the two papers implemented in this thesis and discusses their broader contribution to the literature. A more detailed discussion of methods and results is provided in the two implemented papers.

Niedermayr et al. (2016) investigate the role of regional heterogeneity and spatial interdependence as possible drivers of spatial variations in the adoption of an emerging alternative crop, using the example of the Styrian Oil Pumpkin. They discuss identification issues with respect to model selection and the differentiation between global and local spillover effects and are one of the first papers to estimate a SLX model (Gibbons and Overman, 2012; Halleck-Vega and Elhorst, 2015) in the field of agricultural economics.

Niedermayr et al. (2018) analyse heterogeneous preferences for public goods provided by agriculture in a region of intensive agricultural production. From a methodological point of They apply recent findings in the choice modelling literature, regarding model selection (Hess and Train, 2017) for their econometric analysis. The paper also contributes to the literature on environmental valuation in the context of agriculture, by analysing observed and unobserved preference heterogeneity and MWTP for the PGs groundwater quality, landscape quality and climate stability.

1.3.1 Regional heterogeneity and spatial interdependence as determinants of the cultivation of an emerging alternative crop: The case of the Styrian Oil Pumpkin

Summary and policy relevance[10]

In the course of the liberalisation and globalisation of agricultural markets the CAP of the EU has shifted from quantity-based to quality-based policies, encouraging a diversification of agricultural production. For policy makers it is therefore relevant to better understand the drivers that influence the adoption and spatial distribution of emerging alternative products as well as production systems in agriculture. The aim of the paper was to quantify the determinants

[10] This subsection (summary and policy relevance) is an extended abstract of Niedermayr et al. (2016). It serves primarily as an overview. It does not contain any references to sources used in Niedermayr et al. (2016), although it uses parts of the text of Niedermayr et al. (2016). The full text of the paper with all citations and sources can be found in Chapter 2.

of spatial variations in the cultivation of an emerging alternative crop. For this purpose, the case of the Styrian Oil Pumpkin was selected as an example.

This selection was done for several reasons. First of all, it represents an alternative crop that is undergoing a very dynamic development. Driven by an increasing demand for products from the Styrian Oil Pumpkin, many farmers began to cultivate it or extended their acreage, leading to an increase in oil-pumpkin planted area from about 9000 ha in 1995 to approximately 9800 ha in 2000, 16,000 ha in 2006, 24,000 ha in 2010 and 32,000 ha in 2015. Secondly, the name "Styrian Pumpkin Seed Oil" is registered as a Protected Geographical Indication (PGI) since 1996, limiting the production of Styrian Pumpkin Seed Oil to a defined geographical area. Farmers in that area receive a price premium if they are certified for the production of oil pumpkin according to the specification of the PGI for Styrian Pumpkin Seed oil. Within this PGI area, the cultivation of Styrian Oil Pumpkin is very unevenly distributed and local agglomerations can be identified that may be related to spatial interdependence. Thirdly, the PGI area consists of two separate regions (northern and southern) that differ in terms of production and marketing structure, and are therefore likely to have developed in a different manner in terms of oil-pumpkin cultivation.

Niedermayr et al. (2016) use a unique cross-sectional dataset for their econometric analysis, combining data from various sources (municipality database, IACS database, farm census and Styrian Pumpkin Seed Oil Community Association)[11]. The data is from the year 2010 and covers the 549 municipalities located in the Styrian Oil Pumpkin PGI area. Theoretical considerations as well as information obtained from consultations with experts and local farmers guided the identification of potential drivers of spatial variations in oil-pumpkin cultivation. The independent variables describe the biophysical quality of agricultural land, access to special machinery required for oil-pumpkin production, proximity to stationary washing and drying facilities for oil-pumpkin seeds, production- and marketing conditions (farm size, share of organic farms, livestock density and share of direct marketing farms), subsidies, the education level of farmers and previous presence of oil-pumpkin cultivation. With respect to the presence of spatial effects, talks with the experts also pointed towards the presence of spatial effects in the form of exogenous interaction effects (local spillover effects), influencing spatial variations in oil-pumpkin cultivation. An additional aspect which was found to be important in the talks was the different regional framework-conditions for oil-pumpkin

[11] See Niedermayr et al. (2016) for a detailed list of the respective data sources.

cultivation in the northern and southern part of the PGI area. This led to the decision to estimate two separate regression models for the two regions, as it was hypothesised that the effects of some drivers would be region-specific.

The dependent variable for the analysis was defined as the percentage of arable land cultivated with oil pumpkin in the respective municipality. The general idea for this definition was that it describes the relative profitability of oil-pumpkin cultivation compared to other crops and indirectly also to livestock production, also requiring arable land. As the dependent variable was zero for part of the municipalities, a Tobit model, which takes this sort of censoring into account, was estimated as a basic model and further extended to a SLX Tobit to take possible exogenous interaction effects (local spillover effects) into account.

The findings of Niedermayr et al. (2016) indicate that, apart from (i) crop-specific factors, there are also (ii) region-specific factors such as marketing possibilities and there is (iii) spatial interdependence influencing spatial variations in oil-pumpkin cultivated area. The crop-specific factors consist of basic prerequisites for oil-pumpkin cultivation like favourable natural conditions, proximity to washing and drying facilities for pumpkin seeds and previous experience with oil-pumpkin cultivation. Region-specific factors were found in the form of different production and marketing structures (organic farming in the northern part of the PGI area and direct marketing in the southern part of the PGI area). After controlling for the above mentioned factors, possible interdependence between neighbouring municipalities remained. Specifically, municipalities in the southern PGI-area with a higher share of direct-marketing farms in their neighbourhood have on average a higher percentage of oil-pumpkin cultivated area. This could imply that more direct marketing in neighbouring municipalities **j** attracts more potential customers, and thus has a positive influence on oil-pumpkin cultivation in a municipality **i**. However, the exact channel through which this spatial effect arises, could not be determined based on the available data.

From a policy perspective, the findings of Niedermayr et al. (2016) show the importance of necessary framework conditions for the adoption of an alternative product or production system. The most important prerequisite for the adoption of oil-pumpkin cultivation is access to oil-pumpkin specific infrastructure for farmers (e.g. through shared machinery usage). The different regional production and marketing conditions in the two parts of the PGI area are another relevant factor that can be addressed by policy measures.

Overall, including the spatial dimension – as in this paper the regional context and spatial interdependence – may help to develop a better understanding of the factors driving the adoption process at a local level. Deeper insights such as these are the basis for a more effective targeting of policies aimed at promoting the adoption of alternative products, as well as production systems.

Contribution to the literature and discussion

Spatial econometric models with global spillover-effects have been the main interest for spatial econometricians (LeSage and Pace, 2009) as well as for practitioners, also in agricultural economics (Roe et al., 2002; Anselin et al., 2004; Schmidtner et al., 2012; Garrett et al., 2013). Due to the methodological issues described in section 1.2.1, regarding the limitations of the SAR SAC and GNS model, as well as the general identification issues in more complex models with more than one spatial parameter and the difficulty to assess, which of the models is more suitable, these more complex models have been criticised recently. This criticism was summarised in a special issue of the Journal of Regional Science with contributions from Gibbons and Overman (2012), Corrado and Fingleton (2012) and McMillen (2012).

Gibbons and Overman (2012) focus their critique on the identification of causal effects in spatial econometric models and compare it to the reflection problem, described in Manski (1993). The reflection problem states that based on data of outcomes it is impossible to assess, whether similar individual behaviour is influenced by group behaviour or group characteristics. This is similar to the problem of interpreting the simultaneous movements of a person and her/his reflection in a mirror: without additional knowledge, it is impossible to assess, whether the mirror image causes the movements of the person or reflects them (Manski, 2000). As one solution, Gibbons and Overman (2012) propose to estimate the SLX model when the aim is to analyse potential spatial spillover effects. This does not solve the reflection problem, but is more flexible, requires less assumptions and allows one to narrow down the sources of spatial effects to individual variables. Corrado and Fingleton (2012) focus their criticism on the lack of economic theory in spatial econometric applications and a somewhat mechanical fashion of how variables are introduced in a model or how the spatial weights matrix is specified. McMillen (2012) particularly criticise the SAR model for being used to make causal inference, even though it is just another form of spatial smoothing, which is often used as a quick-fix for misspecification issues related to space. Halleck-Vega and Elhorst (2015) respond to this critique by also proposing the SLX model as a starting point for spatial econometric analyses and emphasising to pay more attention to the specification of the spatial weights matrix.

These developments mark a shift in spatial econometric applications also in the field of agricultural economics, where the SDM (Läpple and Kelley, 2015; Läpple et al., 2017), SDEM

(Lungarska and Chakir, 2018) and the SLX model (Storm et al., 2015) are now applied more often while economic theory and knowledge of the domain under investigation increasingly guide the specification of models and spatial weights matrices.

With respect to spatial effects, Niedermayr et al. (2016) is one of the first empirical applications in agricultural economics, that considers the criticism brought forward by Gibbons and Overman (2012) and follows the approach proposed by Halleck-Vega and Elhorst (2015). One notable exception in this context is the work of Storm et al. (2015), who also apply an SLX model in the context of an analysis of farm structural change in Norway. Instead of letting the data decide based on either Lagrange multiplier tests (Anselin et al., 1996) or Bayesian model comparison (LeSage and Pace, 2009; Lacombe et al., 2014) which (spatial) model has the best fit, Niedermayr et al. (2016) choose the SLX model based on domain knowledge as a flexible yet at the same time less restrictive specification compared to for example the SAR model.

Moreover, the paper uses a rich set of independent variables, based on theoretical considerations information gained from experts and farmers. This dataset is able to describe the otherwise unobserved heterogeneity associated for example with soil- and climate conditions and the presence of oil-pumpkin specific infrastructure, which is also responsible for spatial variations in oil-pumpkin cultivation. Another contribution of the paper is the identification of discrete spatial heterogeneity (Anselin, 2010) through region-specific factors that influence the adoption of an emerging alternative crop in a more complex way than a regional dummy variable would be able to describe. As a result, only one of the spatial lags of the independent variables describing spatial interdependence in the SLX Tobit model remains statistically significant. The paper therefore shows that on an aggregate level, the spatial distribution of oil-pumpkin cultivated area is largely explained by crop-specific factors and regional heterogeneity, if sufficient data, describing the heterogeneity of agroclimatic conditions and the presence of oil-pumpkin specific infrastructure is included. The remaining exogenous interaction effect of direct marketing is not necessarily causal and could also simply describe spatial correlation of the associated independent variable. This approach differs from previous applications (Roe et al., 2002; Holloway et al., 2007; Schmidtner et al., 2012; Garrett et al., 2013), where the model choice was mostly based on goodness of fit and specification tests of competing spatial econometric models.

Despite the described contributions of Niedermayr et al. (2016) to the literature, additional research is necessary to further isolate the channels through which the above described spatial effects operate. One measure that helps to improve identification issues is the use of panel data, as it allows one to better account for path dependency and possible reverse causality problems (Wooldridge, 2010; Elhorst, 2014). Also, promising research uses data on farmers' communication patterns or local farmer groups to build social networks and tries to isolate potential endogenous interaction effects among peers from exogenous interaction effects and other sources of similar group behaviour with instrumental variable techniques (for example Conley and Udry, 2010; Wuepper et al., 2018). However, such research is mostly limited to primary data, based on either (random) samples of the farm population or a very expensive full census of smaller villages/regions.

If 'only' spatially explicit secondary data of farms or administrative regions is available for analysis, an option is to primarily focus on cases, where the type of spatial effect is strongly suggested by the topic of interest, like spatial competition on the land market (Storm et al., 2015) or a strong connection to spatially heterogeneously distributed resources, like in Niedermayr et al. (2016). Storm and Heckelei (2018) present another promising approach for analyses based on secondary data. They expand the SLX model to include two types of spatial lags, one based on local and one based on regional neighbourhood. The regional neighbourhood is used to absorb the effect of spatially correlated omitted variables at a greater scale, which are at the same time correlated with included farm characteristics. This allows them to reduce an omitted variable bias and thus isolate exogenous interaction effects at the micro level.

A final issue related to the identification of spatial effects is artificial spatial autocorrelation, which may be caused by aggregation of data. The modifiable areal unit problem (Openshaw, 1984) or ecological fallacies (Jargowsky, 2005) provide possible explanations for this phenomenon. However, it is also necessary to acknowledge different possible forms of causal spatial interaction at different spatial scales. Research considering these issues has already been carried out in the context of the spatial distribution of organic farming in Germany (Schmidtner et al., 2015) and is also in development for the case of the Styrian Oil Pumpkin, based on initial findings of Niedermayr and Kantelhardt (2017).

1.3.2 Heterogeneous Preferences for Public Goods Provided by Agriculture in a Region of Intensive Agricultural Production: The Case of the Marchfeld

Summary and policy relevance[12]

The aim of Niedermayr et al. (2018) was to elicit the MWTP for the increased provision of public goods provided by agriculture in the Marchfeld, a dynamically developing and semi-urban region in Austria.

Situated between the capitals of Austria (Vienna) and Slovakia (Bratislava), the Marchfeld is a dynamically developing region, which has experienced a strong population growth over the last 10-15 years due to in-migration mostly from urban agglomerations. At the same time, the Marchfeld is marked by an intensive agricultural production with cash-cropping and vegetable production in particular. This production system is to a large extent based on the good soil quality in combination with the possibility for irrigation in the otherwise semi-arid climate of the region, but also leads to negative environmental externalities. Rising societal sensitivity regarding a more sustainable agricultural production is leading to increasing tensions between farmers and other inhabitants, especially in semi-urban regions. Agri-environmental policies, could provide incentives for an extensification of agricultural production, by compensating additional costs and reduced revenues of farmers who decide to increase the provision of public goods. However, current agri-environmental schemes fail in sufficiently addressing these public-good related problems particularly in regions of intensive agricultural production like the Marchfeld. The Marchfeld therefore embodies many of the environmental problems related to agriculture, found within and outside of the EU.

In order to elicit the MWTP of the local population for an increased provision of PGs by agriculture, a DCE was designed in a participatory approach, involving workshops with local stakeholders. In this process, the three PGs groundwater quality, landscape diversity and climate stability, were identified as most relevant for the population and their possible levels were quantified. The DCE was created with a D-optimal orthogonal design (Street et al., 2005), consisting of four blocks, each consisting of 6 choice sets with 2 varying alternatives and a

---

[12] This subsection (summary and policy relevance) is an extended abstract of Niedermayr et al. (2018). It serves primarily as an overview. It does not contain any references to sources used in Niedermayr et al. (2018), although it uses parts of the text of Niedermayr et al. (2018). The full text of the paper with all citations and sources can be found in Chapter 3.

fixed status-quo alternative. The DCE was part of an online survey, that consisted of an introductory section, where the aim and scope of the study were presented, (ii) a section where participants were asked about their attitudes towards the three PGs of interest in the CSR, (iii) the choice experiment to receive information about their preferences and willingness to pay for an improvement in the three above-mentioned PGs, (iv) follow-up questions after the choice experiment to gain information about the motives and beliefs which drove their choices and their general view on PGs and agri-environmental policies, and (v) a section on the socio-demographic characteristics of the participants. The sample was representative with respect to age and gender and consisted of 194 respondents, which were all residents of the Marchfeld.

A CL model served as a basic model specification. Due to high unobserved heterogeneity driving choices, an RPL model was estimated as a second specification and interactions of attributes with socio-demographic factors were included in order to further disentangle heterogeneity in preferences.

A positive and significant MWTP for the improved provision of all three PGs was found, with groundwater quality being most important for the respondents, followed by landscape quality and climate stability. In the case of the Marchfeld, inhabitants of an intensive agricultural production region show a positive MWTP for an improvement in the provision of PGs by agriculture. The results also point out that MWTP varies considerably according to certain socio-economic factors. Specifically, younger respondents show a higher MWTP for an improvement in groundwater quality and climate stability, while older respondents have a higher MWTP for an improved landscape diversity. Furthermore, farmers and incomers (people who have moved to the Marchfeld) show a lower MWTP for improvements in groundwater quality and landscape quality compared to non-farmers and locals.

With respect to policy implications, the article is able to show that an improved provision of PGs is of relevance for the local population of the Marchfeld and for which of the three examined PGs, an improvement is considered as most important. This information is by itself already valuable for political decision makers, as it helps them to identify potential policy priorities in the region. However, the differing preferences of the identified subgroups in the Marchfeld based on socio-demographic characteristics and the found preference heterogeneity, need to be taken into account in this context. Additionally, the higher MWTP of incomers compared to locals should not only be of particular interest for policy-makers responsible for the Marchfeld, but also for policy makers in comparable regions, that are also subject to in-migration from nearby urban areas.

Contribution to the literature and discussion

In choice models based on data from DCEs, the unobserved heterogeneity related to choices is mostly assumed to stem from preference heterogeneity, and RPL models with random preference parameters are estimated to account for this (Train, 2009). Alternatively, the influence of unobserved factors (variance of the error term) on utility could differ over individuals. This is different to the previously described preference heterogeneity, where it is assumed that preferences for the attributes are heterogeneous. This phenomenon is referred to as scale heterogeneity (Hensher et al., 2015). Different models have been proposed, which provide the possibility to capture preference heterogeneity and scale heterogeneity in separate parameters. The most prominent of these is the generalised multinomial logit (GMNL) model (Greene and Hensher, 2010). The notion of separating preference heterogeneity from scale heterogeneity seems indeed tempting. However, Hess and Train (2017) convincingly argue that it is hardly possible to identify scale heterogeneity and preference heterogeneity separately, as both phenomena are not observed from the perspective of the researcher in most cases. They also show that MXL models, which are extended to include correlated random parameters for the attributes, are highly flexible in capturing any form of correlation, including scale heterogeneity and even more flexible than the GMNL model, where the scale heterogeneity is captured in only one parameter. However, they also point out that the source of heterogeneity captured by such a model has to be assumed by the researcher, unless ways are found to better disentangle the different channels through which unobserved heterogeneity arises.

The selection of the econometric model to analyse heterogeneity of choices in Niedermayr et al. (2018) was largely influenced by the arguments of Hess and Train (2017). Niedermayr et al. (2018) is one of the first applications in environmental and agricultural economics, that follows this line of argument (among for example Glenk and Martin-Ortega (2018) or Zhang and Sohngen (2018)). Based on a likelihood-ratio test, the model with additional correlation parameters of the attributes is not significantly different from an RPL model without correlated parameters. This is why the final specification in Niedermayr et al. (2018) is an RPL model without correlation among the random parameters. The standard deviations of the random parameters are explicitly assumed to describe preference heterogeneity.

The inclusion of interaction effects with socio-demographic variables allows one to further disentangle preference heterogeneity. In this context, particularly the finding that newcomers have higher preferences for an increase in groundwater quality, as well as hedges and flower strips on agricultural land has, to the best of the knowledge of the authors, not been made so far. Related studies on the valuation of (ground)water quality (for example Tempesta and Vecchiato, 2013; Meyerhoff et al., 2014) or agrarian landscapes (see for example van Zanten et al. (2014) for an overview of studies or Dupras et al. (2018)) mostly include attributes related to respondents' current place of residence (local or visitor) or at a larger spatial scale, a differentiation between residents of urban and rural areas. One could argue that the found preference heterogeneity with respect to newcomers and locals is caused by correlation with other unobserved socio-demographic characteristics. For example, people who move from a city to the nearby countryside might be predominantly young families with children. However, the estimated RPL model controls for age as well as for the presence of children and does not find any statistically significant relationship. It is therefore more likely that this effect indirectly captures different attitudes of people with urban and rural origin.

Finally, Niedermayr et al. (2018) also provide additional MWTP-estimates for the PGs groundwater quality, landscape quality and climate stability. For example, with respect to groundwater quality the estimated MWTP is comparable to, but lies in the lower range of values found in related studies (Tempesta and Vecchiato, 2013; Latinopoulos, 2014; Tentes and Damigos, 2015). Groundwater shortage is less of an issue in the Marchfeld, but particularly relevant in many of the studies investigating WTP for groundwater. This could explain the lower MWTP for an increase in groundwater quality in the Marchfeld. Regarding greenhouse-gas emission savings, the estimated MWTP also is comparable to findings of related studies (for example Rodríguez-Entrena et al., 2012). However, in general, estimation results of DCEs depend on many different contexts, such as timing and location (Meyerhoff et al., 2014; Tinch et al., 2015), definition, framing and visual representation of the attributes and status-quo alternative (Meyerhoff and Liebe, 2009; Johnston et al., 2017) or design dimensions (Meyerhoff et al., 2015). Particularly with respect to MWTP for the presence of hedges and flower strips, but also for the other PGs investigated, MWTP-estimates are thus highly context-specific.

With respect to unobserved heterogeneity related to choices in DCEs, attitudes of respondents can be included as additional independent variables. This may substantially increase the explanatory power of choice models, but also potentially induces endogeneity, as attitudes may be correlated with other unobserved factors, that are left in the error term. Recent research tries to address this issue by applying a variant of the control-function approach, the multiple indicator solution (MIS) (Costner, 1969; Wooldridge, 2010). The MIS has recently been adapted for choice models by Guevara and Polanco (2016). Some first applications exist in the field of consumer preferences for market goods (Malone and Lusk, 2018) or environmental economics (Mariel et al., 2018), but would be also of great interest in agricultural economics. With such an analysis, it would for example be possible to assess, whether the estimated differences in preferences between locals and newcomers in Niedermayr et al. (2018) are biased.

Framing effects and the effects of the broader context in which a choice experiment is conducted are also highly relevant topics for further research. Findings in behavioural economics increasingly show that the assumption of rational utility maximization does not always hold and that utility is context specific (Tinch et al., 2015). Therefore, the framing of a choice situation (for example by differently formulating an otherwise economically equivalent cost attribute) may lead to misperception, and can thus cause optimizing mistakes of respondents (Brekke et al., 2017; Fosgaard et al., 2017). This is also a potential issue in Niedermayr et al. (2018).

1.4 Conclusions, limitations and outlook

This dissertation addresses two topics in agricultural economics that are of high relevance for agricultural policy: (i) the specialisation of farmers on a niche product with a focus on product origin as well as quality and (ii) multifunctional agriculture, which takes non-market outputs of farms stronger into account. These topics are investigated with econometric models in the context of two case-studies. Niedermayr et al. (2016) analyse spatial variations in the adoption of an emerging alternative crop with spatial econometric models in order to better understand the drivers, influencing the focus on a niche product with an emphasis on product origin and quality. Niedermayr et al. (2018) analyse the heterogeneous demand for an increased provision of environmental PGs as one aspect of multifunctional agriculture with choice models based on a DCE. In this thematic context, the broader aim of the thesis is to discuss the applicability of spatial econometric models and discrete choice models based on DCEs and possibilities to analyse different sources of heterogeneous outcomes with both methods, taking recent methodological developments into account.

A first general conclusion is that the issue of identification of the sources of heterogeneous outcomes represents an analogy between spatial econometrics and discrete choice modelling: the channels through which such heterogeneity arises are simply unobserved in most empirical settings. A clear differentiation between spatial interdependence and spatial heterogeneity on the one hand, as well as between preference heterogeneity and scale heterogeneity on the other hand remains therefore challenging.

However, the results of the two case-studies also show that incorporating comprehensive case-specific knowledge into the research process helps to narrow down the possible sources of heterogeneity. In both papers, valuable information is acquired for example through talks with experts and members of the respective population of interest or workshops. Such information provides vital guidance in many steps of the research process, ranging from the specification of the econometric model and the choice experiment as well as the interpretation and discussion of results, to the drawing of case-relevant conclusions and formulations of policy recommendations.

Despite the described contributions to the literature several shortcomings remain. While the more specific issues are addressed in the previous sections and in the respective papers, the focus here lies on more general issues. A first issue is that the knowledge gained from experts or locals on case-specific issues may also be subject to a bias. This implies that such information should not be taken as a fact and has to be critically questioned and cross-checked regarding for example biased viewpoints of the sources. A second aspect relates to the chosen focus on two case-studies. While it provides helpful insights for the respective case, a generalisation of such findings is hardly possible and can be attained only to a limited extent by a greater number of studies. A final aspect is that despite the increased understanding of the case-specific processes, both analyses are unable to provide a definite causal explanation of their findings.

Therefore, further research in both fields is necessary. Several possibilities have been outlined in the previous subsections for both methods. At a more general level, a promising avenue for future research is to combine aspects of both methodologies and investigate spatial effects in a choice experiment. Interest in this notion has been steadily increasing in the literature (see Johnston et al. (2015) for an overview of studies). For example, Sagebiel et al. (2017) show that the demand for afforestation policies expressed in WTP is negatively correlated to the current endowment with forest area at the place of residence of respondents. Investigating these spatial effects in choice experiments with other PGs related to agriculture could provide valuable insights in the spatial dimension of preferences for PGs.

1.5 References

Adamowicz, W., Boxall, P., Williams, M., Louviere, J., 1998a. Stated Preference Approaches for Measuring Passive Use Values: Choice Experiments and Contingent Valuation. American Journal of Agricultural Economics 80 (1), 64–75.

Adamowicz, W., Louviere, J., Swait, J., 1998b. Introduction to Attribute-Based Stated Choice Methods. Final Report to Resource Valuation Branch, Damage Assessment Center, NOAA, U.S. Department of Commerce, 44 pp.

Adamowicz, W., Louviere, J., Williams, M., 1994. Combining Revealed and Stated Preference Methods for Valuing Environmental Amenities. Journal of Environmental Economics and Management 26 (3), 271–292.

Albert, J.H., Chib, S., 1993. Bayesian Analysis of Binary and Polychotomous Response Data. Journal of the American Statistical Association 88 (422), 669.

Albuquerque, T.G., Oliveira, M.B.P., Costa, H.S., 2018. 25 years of European Union (EU) quality schemes for agricultural products and foodstuffs across EU Member States (eng). Journal of the science of food and agriculture 98 (7), 2475–2489.

Anselin, L., 1988. Spatial Econometrics: Methods and Models. Springer, Netherlands.

Anselin, L., 2003. Spatial Externalities, Spatial Multipliers, And Spatial Econometrics. International Regional Science Review 26 (2), 153–166.

Anselin, L., 2010. Thirty years of spatial econometrics. Papers in Regional Science 89 (1), 3–25.

Anselin, L., Bera, A.K., Florax, R., Yoon, M.J., 1996. Simple diagnostic tests for spatial dependence. Regional Science and Urban Economics 26 (1), 77–104.

Anselin, L., Bongiovanni, R., Lowenberg-DeBoer, J., 2004. A Spatial Econometric Approach to the Economics of Site-Specific Nitrogen Management in Corn Production. American Journal of Agricultural Economics 86 (3), 675–687.

Aprile, M.C., Caputo, V., Nayga Jr, R.M., 2012. Consumers' valuation of food quality labels: the case of the European geographic indication and organic farming labels. International Journal of Consumer Studies 36 (2), 158–165.

Arentze, T., Borgers, A., Timmermans, H., DelMistro, R., 2003. Transport stated choice responses: effects of task complexity, presentation format and literacy. Transportation Research Part E: Logistics and Transportation Review 39 (3), 229–244.

Bartolini, F., Viaggi, D., 2013. The common agricultural policy and the determinants of changes in EU farm size. Land Use Policy 31, 126–135.

Bhat, C.R., 1995. A heteroscedastic extreme value model of intercity travel mode choice. Transportation Research Part B: Methodological 29 (6), 471–483.

Blow, L., Blundell, R., 2018. A Nonparametric Revealed Preference Approach to Measuring the Value of Environmental Quality. Environmental and Resource Economics 69 (3), 503–527.

Brekke, K.A., Konow, J., Nyborg, K., 2017. Framing in a threshold public goods experiment with heterogeneous endowments. Journal of Economic Behavior & Organization 138, 99–110.

Carlsson, F., Frykblom, P., Lagerkvist, C.J., 2007. Consumer willingness to pay for farm animal welfare: mobile abattoirs versus transportation to slaughter. Eur Rev Agric Econ 34 (3), 321–344.

ChoiceMetrics, 2014. Ngene 1.1.2 user manual & reference guide. ChoiceMetrics Pty Ltd.

Clark, M.D., Determann, D., Petrou, S., Moro, D., Bekker-Grob, E.W. de, 2014. Discrete choice experiments in health economics: a review of the literature (eng). PharmacoEconomics 32 (9), 883–902.

Conley, T.G., Udry, C.R., 2010. Learning about a New Technology: Pineapple in Ghana. American Economic Review 100 (1), 35–69.

Corrado, L., Fingleton, B., 2012. Where is the economics in spatial econometrics? Journal of Regional Science 52 (2), 210–239.

Costner, H.L., 1969. Theory, Deduction, and Rules of Correspondence. American Journal of Sociology 75 (2), 245–263.

Dupras, J., Laurent-Lucchetti, J., Revéret, J.-P., DaSilva, L., 2018. Using contingent valuation and choice experiment to value the impacts of agri-environmental practices on landscapes aesthetics. Landscape Research 43 (5), 679–695.

Elhorst, J.P., 2010. Applied Spatial Econometrics: Raising the Bar. Spatial Economic Analysis 5 (1), 9–28.

Elhorst, J.P., 2014. Spatial Econometrics: From Cross-Sectional Data to Spatial Panels. Springer, Heidelberg New York Dordrecht London.

Espinosa-Goded, M., Barreiro-Hurlé, J., Ruto, E., 2010. What Do Farmers Want From Agri-Environmental Scheme Design? A Choice Experiment Approach. J Agric Econ 61 (2), 259–273.

European Commission, 2017. The Future of Food and Farming. European Union, Brussels. https://ec.europa.eu/agriculture/sites/agriculture/files/future-of-cap/future_of_food_and_farming_communication_en.pdf (accessed 12 January 2018).

Feder, G., Umali, D.L., 1993. The adoption of agricultural innovations. Technological Forecasting and Social Change 43 (3-4), 215–239.

Feichtinger, P., Salhofer, K., 2016. The Fischler Reform of the Common Agricultural Policy and Agricultural Land Prices. Land Economics 92 (3), 411–432.

Fosgaard, T.R., Hansen, L.G., Wengström, E., 2017. Framing and Misperception in Public Good Experiments. Scand. J. of Economics 119 (2), 435–456.

Garrett, R.D., Lambin, E.F., Naylor, R.L., 2013. Land institutions and supply chain configurations as determinants of soybean planted area and yields in Brazil. Land Use Policy 31, 385–396.

Gellrich, M., Zimmermann, N.E., 2007. Investigating the regional-scale pattern of agricultural land abandonment in the Swiss mountains: a spatial statistical modelling approach. Landscape and Urban Planning 79 (1), 65–76.

Getis, A., 2009. Spatial Weights Matrices. Geographical Analysis 41 (4), 404–410.

Gibbons, S., Overman, H.G., 2012. Mostly Pointless Spatial Econometrics? Journal of Regional Science 52 (2), 172–191.

Glenk, K., Martin-Ortega, J., 2018. The economics of peatland restoration. Journal of Environmental Economics and Policy, 1–18.

Golgher, A.B., Voss, P.R., 2016. How to Interpret the Coefficients of Spatial Models: Spillovers, Direct and Indirect Effects. Spatial Demography 4 (3), 175–205.

Greene, W.H., Hensher, D.A., 2010. Does scale heterogeneity across individuals matter? An empirical assessment of alternative logit models. Transportation 37 (3), 413–428.

Guevara, C.A., Polanco, D., 2016. Correcting for endogeneity due to omitted attributes in discrete-choice models: The multiple indicator solution. Transportmetrica A: Transport Science 12 (5), 458–478.

Halleck-Vega, S., Elhorst, J.P., 2015. The SLX Model. Journal of Regional Science 55 (3), 339–363.

Hensher, D.A., 2010. Hypothetical bias, choice experiments and willingness to pay. Transportation Research Part B: Methodological 44 (6), 735–752.

Hensher, D.A., Rose, J.M., Greene, W.H., 2015. Applied choice analysis (eng), Second edition ed. Cambridge University Press, Cambridge, 1188 pp.

Hess, S., Train, K., 2017. Correlation and scale in mixed logit models. Journal of Choice Modelling 23, 1–8.

Holloway, G., Lacombe, D., LeSage, J.P., 2007. Spatial Econometric Issues for Bio-Economic and Land-Use Modelling. Journal of Agricultural Economics 58 (3), 549–588.

Hoyos, D., 2010. The state of the art of environmental valuation with discrete choice experiments. Ecological Economics 69 (8), 1595–1603.

Jargowsky, P.A., 2005. Ecological Fallacy. In: Kempf-Leonard, K. (Ed.), Encyclopedia of social measurement, vol. 1. Elsevier, Amsterdam, 715–722.

Johnston, R.J., Boyle, K.J., Adamowicz, W., Bennett, J., Brouwer, R., Cameron, T.A., Hanemann, W.M., Hanley, N., Ryan, M., Scarpa, R., Tourangeau, R., Vossler, C.A., 2017. Contemporary Guidance for Stated Preference Studies. Journal of the Association of Environmental and Resource Economists 4 (2), 319–405.

Johnston, R.J., Jarvis, D., Wallmo, K., Lew, D.K., 2015. Multiscale Spatial Pattern in Nonuse Willingness to Pay: Applications to Threatened and Endangered Marine Species. Land Economics 91 (4), 739–761.

Kallas, Z., Gómez-Limón, J.A., Arriaza, M., 2007. Are citizens willing to pay for agricultural multifunctionality? Agricultural Economics 36 (3), 405–419.

Knowler, D., Bradshaw, B., 2007. Farmers' adoption of conservation agriculture: A review and synthesis of recent research. Food Policy 32 (1), 25–48.

Krinsky, I., Robb, A.L., 1986. On Approximating the Statistical Properties of Elasticities. The Review of Economics and Statistics 68 (4), 715.

Krugman, P., 1991. Geography and Trade. The MIT Press, Cambridge.

Kuhfeld, W.F., Tobias, R.D., Garratt, M., 1994. Efficient Experimental Design with Marketing Research Applications. Journal of Marketing Research 31 (4), 545.

Lacombe, D.J., Holloway, G.J., Shaughnessy, T.M., 2014. Bayesian Estimation of the Spatial Durbin Error Model with an Application to Voter Turnout in the 2004 Presidential Election. International Regional Science Review 37 (3), 298–327.

Lancaster, K.J., 1966. A New Approach to Consumer Theory. Journal of Political Economy 74 (2), 132–157.

Läpple, D., Holloway, G., Lacombe, D.J., O'Donoghue, C., 2017. Sustainable technology adoption: A spatial analysis of the Irish Dairy Sector. European Review of Agricultural Economics 44 (5), 810–835.

Läpple, D., Kelley, H., 2015. Spatial dependence in the adoption of organic drystock farming in Ireland. European Review of Agricultural Economics 42 (2), 315–337.

Latinopoulos, D., 2014. Using a choice experiment to estimate the social benefits from improved water supply services. Journal of Integrative Environmental Sciences 11 (3-4), 187–204.

LeSage, J.P., 1997. Bayesian Estimation of Spatial Autoregressive Models. International Regional Science Review 20 (1-2), 113–129.

LeSage, J.P., 2014. What Regional Scientists Need to Know about Spatial Econometrics. The Review of Regional Studies (44), 13–32.

LeSage, J.P., Pace, R.K., 2009. Introduction to Spatial Econometrics. CRC Press, Boca Raton.

Lippert, C., 2006. Zur Relevanz der 'Neuen Wirtschaftsgeografie' für den deutschen Agrarsektor. http://www.uni-goettingen.de/docs/d03ea1eb73be3493f6840ad61b3ead83.pdf (accessed 25 July 2018).

Louviere, J.J., 2006. What You Don't Know Might Hurt You: Some Unresolved Issues in the Design and Analysis of Discrete Choice Experiments. Environ Resource Econ 34 (1), 173–188.

Louviere, J.J., Hensher, D.A., 1982. Design and Analysis of Simulated Choice or Allocation Experiments in Travel Choice Modeling. Transportation Research Record (890), 11–17.

Louviere, J.J., Woodworth, G., 1983. Design and Analysis of Simulated Consumer Choice or Allocation Experiments: An Approach Based on Aggregate Data. Journal of Marketing Research 20 (4), 350.

Lungarska, A., Chakir, R., 2018. Climate-induced Land Use Change in France: Impacts of Agricultural Adaptation and Climate Change Mitigation. Ecol Econ Ecol Econ 147, 134–154.

Malone, T., Lusk, J.L., 2018. An instrumental variable approach to distinguishing perceptions from preferences for beer brands. Manage Decis Econ 32 (1), 65.

Manski, C., 2000. Economic Analysis of Social Interactions. Journal of Economic Perspectives 14 (3), 115–136.

Manski, C.F., 1993. Identification of Endogenous Social Effects: The Reflection Problem. The Review of Economic Studies 60 (3), 531.

Mariel, P., Hoyos, D., Artabe, A., Guevara, C.A., 2018. A multiple indicator solution approach to endogeneity in discrete-choice models for environmental valuation (eng). The Science of the total environment 633, 967–980.

McFadden, D., 1974. Conditional logit analysis of qualitative choice behavior. In: Zarembka, P. (Ed.), Frontiers in Econometrics. Academic Press, New York.

McFadden, D., Train, K., 2000. Mixed MNL models for discrete response. J. Appl. Econ. 15 (5), 447–470.

McMillen, D.P., 2012. Perspectives on spatial econometrics: linear smoothing with structured models. Journal of Regional Science 52 (2), 192–209.

Meyerhoff, J., Boeri, M., Hartje, V., 2014. The value of water quality improvements in the region Berlin–Brandenburg as a function of distance and state residency. Water Resources and Economics 5, 49–66.

Meyerhoff, J., Liebe, U., 2009. Status Quo Effect in Choice Experiments: Empirical Evidence on Attitudes and Choice Task Complexity. Land Economics (85(3)), 515–528.

Meyerhoff, J., Oehlmann, M., Weller, P., 2015. The Influence of Design Dimensions on Stated Choices in an Environmental Context. Environ Resource Econ 61 (3), 385–407.

Niedermayr, A., Kantelhardt, J., 2017. 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. 15th EAAE congress. European Association of Agricultural Economists (EAAE), Parma, Italy.

Niedermayr, A., Kapfer, M., Kantelhardt, J., 2016. Regional heterogeneity and spatial interdependence as determinants of the cultivation of an emerging alternative crop: The case of the Styrian Oil Pumpkin. Land Use Policy 58, 276–288.

Niedermayr, A., Schaller, L., Mariel, P., Kieninger, P., Kantelhardt, J., 2018. Heterogeneous Preferences for Public Goods Provided by Agriculture in a Region of Intensive Agricultural Production: The Case of the Marchfeld. Sustainability 10 (6), 2061.

Openshaw, S., 1984. Ecological Fallacies and the Analysis of Areal Census Data. Environment and Planning A 16 (1), 17–31.

Ord, K., 1975. Estimation Methods for Models of Spatial Interaction. Journal of the American Statistical Association 70 (349), 120.

Pace, R.K., Zhu, S., 2012. Separable spatial modeling of spillovers and disturbances. Journal of Geographical Systems 14 (1), 75–90.

Paelinck, J.H.P., Klaassen, L.H., 1979. Spatial econometrics (eng). Gower, Farnborough, 211 pp.

Ragkos, A., Theodoridis, A., 2016. Valuation of environmental and social functions of the multifunctional Cypriot agriculture. Land Use Policy 54, 593–601.

Randall, A., 2002. Valuing the outputs of multifunctional agriculture. European Review of Agriculture Economics 29 (3), 289–307.

Rodríguez-Entrena, M., Barreiro-Hurlé, J., Gómez-Limón, J.A., Espinosa-Goded, M., Castro-Rodríguez, J., 2012. Evaluating the demand for carbon sequestration in olive grove soils as a strategy toward mitigating climate change (eng). Journal of environmental management 112, 368–376.

Roe, B., Irwin, E.G., Sharp, J.S., 2002. Pigs in space: modeling the spatial structure of hog production in traditional and nontraditional production regions (eng). American Journal of Agricultural Economics 84 (2), 259–278.

Ryan, M., Gerard, K., Amaya-Amaya, M., 2008. Discrete Choice Experiments in a Nutshell. In: Bateman, I.J., Ryan, M., Gerard, K., Amaya-Amaya, M. (Eds.), Using Discrete Choice Experiments to Value Health and Health Care: The Economics of Non-Market Goods and Resources, vol. 11. Springer, Dordrecht, pp. 13–46.

Sagebiel, J., Glenk, K., Meyerhoff, J., 2017. Spatially explicit demand for afforestation. Forest Policy and Economics 78, 190–199.

Samuelson, P.A., 1954. The Pure Theory of Public Expenditure. The Review of Economics and Statistics 36 (4), 387.

Schmidtner, E., Lippert, C., Dabbert, S., 2015. Does Spatial Dependence Depend on Spatial Resolution?: An Empirical Analysis of Organic Farming in Southern Germany. German Journal of Agricultural Economics 64 (3), 175–191.

Schmidtner, E., Lippert, C., Engler, B., Haring, A.M., Aurbacher, J., Dabbert, S., 2012. Spatial distribution of organic farming in Germany: Does neighbourhood matter? European Review of Agricultural Economics 39 (4), 661–683.

Storm, H., Heckelei, T., 2018. Reducing omitted-variable bias in spatial-interaction models by considering multiple neighbourhoods. Spatial Economic Analysis 41 (1), 1–16.

Storm, H., Mittenzwei, K., Heckelei, T., 2015. Direct Payments, Spatial Competition, and Farm Survival in Norway. American Journal of Agricultural Economics 97 (4), 1192–1205.

Street, D.J., Burgess, L., Louviere, J.J., 2005. Quick and easy choice sets: Constructing optimal and nearly optimal stated choice experiments. International Journal of Research in Marketing 22 (4), 459–470.

Tempesta, T., Vecchiato, D., 2013. Riverscape and groundwater preservation: a choice experiment (eng). Environmental management 52 (6), 1487–1502.

Tentes, G., Damigos, D., 2015. Discrete Choice Experiment for Groundwater Valuation: Case of the Asopos River Basin, Greece. J. Water Resour. Plann. Manage. 141 (7), 4014089.

Tinch, D., Colombo, S., Hanley, N., 2015. The Impacts of Elicitation Context on Stated Preferences for Agricultural Landscapes. J Agric Econ 66 (1), 87–107.

Train, K.E., 2009. Discrete Choice Methods with Simulation. Cambridge University Press, Cambridge.

Useche, P., Barham, B.L., Foltz, J.D., 2009. Integrating Technology Traits and Producer Heterogeneity: A Mixed-Multinomial Model of Genetically Modified Corn Adoption. Am J Agr Econ Am J Agr Econ 91 (2), 444–461.

Van der Ploeg, J.D., Ventura, F., Milone, P., Biró, S., Dudás, G., Fieldsend, A., Fogarasi, J., Hamaza, E., Miskó, K., Kürthy, G., Potori, N., Rácz, K., Tikász, I., Tóth, O., Vágó, S., Varga, E., Varga, E., Sorrentino, A., Rosso, C., Cacchiarelli, L., 2016. Research for AGRI Committee - Structural Change in EU farming: how can the CAP support a 21st Century European model of agriculture?

van Zanten, B.T., Verburg, P.H., Espinosa, M., Gomez-y-Paloma, S., Galimberti, G., Kantelhardt, J., Kapfer, M., Lefebvre, M., Manrique, R., Piorr, A., Raggi, M., Schaller, L., Targetti, S., Zasada, I., Viaggi, D., 2014. European agricultural landscapes, common agricultural policy and ecosystem services: a review. Agronomy for Sustainable Development 34 (2), 309–325.

Viaggi, D., Raggi, M., Bartolini, F., Sardonini, L., 2013. Spatial Patterns of Change in Agriculture and the Role of the Common Agricultural Policy. Outlook Agric 42 (1), 25–32.

Walker, J.L., Wang, Y., Thorhauge, M., Ben-Akiva, M., 2018. D-efficient or deficient?: A robustness analysis of stated choice experimental designs. Theory Decis 84 (2), 215–238.

Williams, H.C.W.L., 1977. On the Formation of Travel Demand Models and Economic Evaluation Measures of User Benefit. Environment and Planning A 9 (3), 285–344.

Wooldridge, J.M., 2010. Econometric analysis of cross section and panel data, 2nd ed. ed. MIT Press, Cambridge, Mass., xxvii, 1064.

Wuepper, D., Sauer, J., Kleemann, L., 2018. Sustainable intensification amongst Ghana's pineapple farmers: the complexity of an innovation determines the effectiveness of its training. Environment and Development Economics 23 (01), 98–119.

Zanoli, R., Scarpa, R., Napolitano, F., Piasentier, E., Naspetti, S., Bruschi, V., 2013. Organic label as an identifier of environmentally related quality: A consumer choice experiment on beef in Italy. Renew. Agric. Food Syst. 28 (01), 70–79.

Zasada, I., 2011. Multifunctional peri-urban agriculture—A review of societal demands and the provision of goods and services by farming. Land Use Policy 28 (4), 639–648.

Zhang, W., Sohngen, B., 2018. Do U.S. Anglers Care about Harmful Algal Blooms? A Discrete Choice Experiment of Lake Erie Recreational Anglers. Am J Agr Econ Am J Agr Econ 100 (3), 868–888.

1.6 Overview of published papers implemented in the thesis

The next two chapters of the cumulative dissertation comprises the following two publications, with the author of this thesis as the first author. Both publications were published in journals with impact factor according to SCI/SSCI[13].

*Note: **Peer reviewed publications listed in SCI/SSCI*

**Niedermayr, A., Kapfer, M., Kantelhardt, J., 2016. Regional heterogeneity and spatial interdependence as determinants of the cultivation of an emerging alternative crop: The case of the Styrian Oil Pumpkin. Land Use Policy 58, 276–288. https://doi.org/10.1016/j.landusepol.2016.07.033. (Impact Factor 2017: 3.194).

**Niedermayr, A., Schaller, L., Mariel, P., Kieninger, P., Kantelhardt, J., 2018. Heterogeneous Preferences for Public Goods Provided by Agriculture in a Region of Intensive Agricultural Production: The Case of the Marchfeld. Sustainability 10 (6), 2061. https://doi.org/10.3390/su10062061. (Impact Factor 2017: 2.075)

---

[13] Due to formatting reasons the two publications are presented without the layout of the publishers. The numeration of the chapters, figures, tables and formulas was adapted to reflect the structure of the thesis. The formatting of the formulas was also adapted to that of the framework-article. Additionally, the spelling in the second article was changed from American English to British English.

2 Regional heterogeneity and spatial interdependence as determinants of the cultivation of an emerging alternative crop: The case of the Styrian Oil Pumpkin

Abstract:

In the course of the liberalisation and globalisation of agricultural markets the Common Agricultural Policy (CAP) of the European Union (EU) has shifted from quantity-based to quality-based policies, encouraging a diversification of agricultural production. For policy makers it is therefore relevant to understand better the drivers which influence the adoption and spatial distribution of emerging alternative products and production systems in agriculture. Taking the Styrian Oil Pumpkin as an example, the aim of this study is to quantify the determinants of spatial variations in the cultivation of an emerging alternative crop. We estimate Tobit and SLX Tobit models for two regions, drawing on cross-sectional data from the year 2010 of 549 municipalities in the Styrian Oil Pumpkin Protected Geographical Indication (PGI) area. Our findings indicate that, apart from (i) crop specific factors, there are also (ii) region specific factors such as marketing possibilities and there is (iii) spatial interdependence influencing spatial variations in oil pumpkin cultivated area and we conclude that these factors also need to be considered for the support of other emerging alternative products and production systems in agriculture.

Keywords: Styrian Oil Pumpkin, PGI, regional heterogeneity, spillover, spatial econometrics, SLX Tobit model

2.1 Introduction

In recent decades, the ongoing liberalisation and globalisation of agricultural markets have led to agriculture in the European Union (EU) being increasingly exposed to competition from the world market (McNamara and Weiss, 2005; Thompson et al., 2000). In response to this development, farmers have chosen different strategies, ranging from farm growth and intensification (Bartolini and Viaggi, 2013; Weiss, 1999), farm exit or part-time farming (Raggi et al., 2013) to the diversification of agricultural production (McNamara and Weiss, 2005). The latter strategy has led to a growing interest in alternative production systems such as organic farming (Darnhofer et al., 2005) or emerging alternative products like regional food products (Lamarque and Lambin, 2015; Tregear et al., 2007). This marks a shift in the EU's Common Agricultural Policy (CAP) from quantity-based to quality-based policies.

In the literature, a variety of factors has been identified which influences the adoption and spatial distribution of alternative products or production systems in agriculture. However, the relevant factors depend to a great extent on the specific product/production system and it is therefore difficult to summarise them at a general level (Knowler and Bradshaw, 2007). For example, adopting a new seed variety of a crop which is already cultivated is less complicated than, and depends on different factors compared to, the adoption of a new crop which requires special machinery and is therefore associated with higher transition costs (Pannell et al., 2006).

Aside from the context of the product or production system, one aspect which has received less attention in empirical research is the regional context of the analysis. The drivers which affect the adoption of a product or production system may, for example, differ among regions within a study area due to heterogeneous preconditions for agricultural production (Useche et al., 2009). Another source of heterogeneity in adoption which is recognised in the theoretical literature (Pannell et al., 2006) but also mainly not considered in empirical studies is spatial interdependence – meaning any form of strategic interaction, indirect effect or spatial correlation among neighbouring observations (Storm et al., 2015). If spatial interdependence is not considered in an empirical analysis, this can lead to biased results (LeSage, 2009).

The present study focuses on these two aspects as sources of heterogeneity in the adoption of a product/production system, thereby filling an existing knowledge gap in the current literature. Specifically, we aim to analyse the spatial distribution of an alternative crop, considering (i) the crop-specific context, (ii) the region-specific context and (iii) spatial interdependence. For our analysis we choose the cultivation of Styrian Oil Pumpkin in Austria as an example[14]. This is for several reasons. First of all, it is an alternative crop which is currently undergoing a very dynamic development. Secondly, since 1996 the name "Styrian Pumpkin Seed Oil" is registered as a Protected Geographical Indication (PGI), which limits the production of Styrian Pumpkin Seed Oil to a defined area (European Union, 1995). Within this PGI area, the cultivation of Styrian Oil Pumpkin is very unevenly distributed and local agglomerations can be identified which may be related to spatial interdependence. Thirdly, the PGI area consists of two separate regions (northern and southern), which differ in terms of production and marketing structure and are therefore likely to have developed in a different manner in terms of oil-pumpkin cultivation. To the best of our knowledge, no previous study has analysed the determinants of spatial variations in the cultivation of an emerging alternative crop, considering all of the above-mentioned aspects[15]. However, from a policy perspective, we think that including the spatial dimension in such an analysis – in our case the regional context and spatial interdependence – leads to a better understanding of the drivers of alternative products, as well as production systems, and this therefore enables a more effective targeting of policies aimed at promoting their diffusion. Piorr and Viaggi (2015) follow the same line of argument in the context of rural-development policy evaluation.

For the analysis we apply an econometric approach. This decision is based on the fact that we have previously gathered valuable information on the possible drivers of oil pumpkin production from discussions with experts. Additionally, we have access to a unique cross-sectional dataset from the year 2010, comprising biophysical, socio-economic and infrastructural data from 563 municipalities located in the PGI area. Due to a high proportion of zeroes in the dependent variable (the percentage of arable land cultivated with oil pumpkin), we apply a Tobit model (Wooldridge, 2012). To consider regional differences, we estimate separate models for the northern and southern region of the PGI area, using the same set of independent variables. As a final step, we control our results for the presence of spatial interdependence which may lead to positive or negative externalities, by additionally estimating a Spatial Lag of X (SLX) model, introduced by LeSage (2009) and recently also advocated by Halleck Vega and Elhorst (2015).

---

[14] Throughout the text we refer to the Styrian Oil Pumpkin when we use the term "oil pumpkin".

[15] We would here point out that it is not the aim of this study to evaluate the PGI for Styrian Pumpkin Seed Oil as it is done for other products in other analyses (e.g. Lamarque and Lambin, 2015; or Quetier et al., 2005).

The structure of the paper is as follows: in the next section, we present a brief literature review and put forward our basic econometric model. We then introduce our case study, the Styrian Oil Pumpkin, and describe our data basis, as well as the model variables. We proceed to the presentation and discussion of our results and, finally, we provide concluding remarks.

2.2 Methodology

2.2.1 Background information on the adoption and spatial distribution of emerging products and production systems in agriculture

The literature which analyses the adoption and spatial distribution of emerging products and production systems in agriculture comprises production systems such as organic farming (Padel, 2001; Schmidtner et al., 2012) or conservation agriculture (Arslan et al., 2014; Rodríguez-Entrena and Arriaza, 2013) and products like switchgrass (Jensen et al., 2007) or soy (Garrett et al., 2013). Essentially, the aim of such studies is to quantify the drivers which influence the adoption of, and therefore also determine the spatial distribution of, emerging production systems and products with different econometric models.

An initial type of study which has developed from the analysis of technology adoption (e.g. Lindner, 1987) focuses on adoption as a decision process. For example, Abadi Ghadim and Pannell (1999) develop a conceptual framework of individual farmers' decisions to adopt a new crop and they emphasise the importance of learning, risk perception and uncertainty. In an application of their framework (Abadi Ghadim et al., 2005), where the adoption of chickpeas in Western Australia is analysed, it is pointed out that adoption depends on economic motives as well as how risky farmers perceive the crop to be and whether the farmers have previous experience with the crop. Other studies which focus more on farm and farmer characteristics identify, for example, farm size, farm profitability, access to credit, the biophysical quality of land or the age and level of education of the farmer as relevant factors for adoption (for an overview see e.g. Knowler and Bradshaw, 2007; or Pannell et al., 2006; for an application see e.g. Rodríguez-Entrena and Arriaza, 2013). However, all these factors are very heterogeneous, because they vary, for example, with the product or production system of interest or the historical and cultural background of regions (Knowler and Bradshaw, 2007). One of the few studies which takes regional heterogeneity into account is by Useche et al. (2009), who discover that the factors which influence the adoption of improved maize varieties vary among different regions in the USA. A central finding of our literature review is therefore that research should focus on identification of crop-specific instead of universally applicable factors and should also take into account the regional heterogeneity of factors and their respective effects on adoption.

A second branch of literature concentrates on the role of spatial interdependence in explaining heterogeneity in the spatial distribution of a crop or production system. The basic idea is that adoption (e.g. planting of a new crop) and intensity of adoption (e.g. share of suitable arable land planted with a new crop) also depend on what happens in the neighbourhood. Such analyses mostly apply spatial regression models which relax the assumption – usually imposed by non-spatial regression models – that observations are independent from one another. Investigation in this area comprises, for example, the spatial distribution of major agricultural products like dairy and pig production (Isik, 2004; Roe et al., 2002) and soy and maize cultivation (Garrett et al., 2013; Odgaard et al., 2011), as well as alternative production systems like organic farming (Läpple and Kelley, 2015; Schmidtner et al., 2015; Schmidtner et al., 2012). For example, Garrett et al. (2013) analyse the determinants of soybean cultivation in Brazil with a cross-sectional spatial lag model at the county level. Their main findings are that beneficial biophysical conditions, which lead to higher yields and certain supply-chain configurations (co-operative membership and access to credit), promote soybean cultivation. Schmidtner et al. (2015) analyse spatial variations in organic farming in the German federal states of Bavaria and Baden-Württemberg at municipal and county levels, also with cross-sectional data. They find that less favourable climatic conditions and a favourable social and political environment have a positive influence on the share of organic farms in a municipality/county and they conclude that the share of organic farms also depends on the share of organic farms in neighbouring municipalities or counties – implying the presence of spatial interdependence.

2.2.2 Econometric model

One common feature of most adoption studies is that only part of the farmers has adopted the product/production system. Therefore, the use of a linear model estimated by ordinary least squares (OLS) would lead to biased results due to censoring (Wooldridge, 2012). The choice of the appropriate regression model depends, moreover, on the extent of information available for the dependent variable. If the only available information is whether an adoption has or has not taken place (e.g. planting of a new crop), then binary response (Probit- or Logit-) models are appropriate (e.g. Boulay et al., 2012). However, if the available information also covers the intensity of adoption (e.g. the share of arable land planted with the new crop), which also applies in our case, this additional information should be exploited. We therefore use a Tobit model which takes censoring into account and is also often applied in similar studies (e.g. Consmüller et al., 2010; Jensen et al., 2007; Langyintuo and Mekuria, 2008). The Tobit model expresses the dependent variable $\mathbf{Y}$ of a linear regression model in combination with an underlying latent variable $\mathbf{Y}^*$ (Wooldridge, 2012):

$$\mathbf{Y}^* = \boldsymbol{\alpha}\boldsymbol{\iota}_\mathbf{N} + \mathbf{X}\boldsymbol{\beta} + \mathbf{u} \text{ where } \mathbf{y_i} = \mathbf{y_i^*} \text{ if } \mathbf{y_i^*} > \mathbf{0} \text{ and } \mathbf{y_i} = \mathbf{0} \text{ if } \mathbf{y_i^*} \leq \mathbf{0} \tag{10}$$

In this model $\boldsymbol{\alpha}$ is a constant term, which is multiplied with a vector of ones $\boldsymbol{\iota}_\mathbf{N}$, $\mathbf{X}$ is a matrix with the n values of the $\mathbf{k}$ independent variables, $\boldsymbol{\beta}$ is a vector of k regression coefficients and $\mathbf{u}$ is a vector of $\mathbf{n}$ normally distributed errors with variance $\boldsymbol{\sigma}^\mathbf{2}$. The Tobit model is estimated using maximum likelihood.

In contrast to an OLS regression, the partial effect of an independent variable $\mathbf{x_k}$ on the dependent variable $\mathbf{Y}$ in a Tobit model varies with the values taken on by all independent variables $\mathbf{X}$. We therefore utilise the partial effect at the average (PEA), which expresses the effect of $\mathbf{x_k}$ on $\mathbf{Y}$ when all independent variables $\mathbf{X}$ are evaluated at their mean. It is calculated by multiplying Tobit coefficients with an adjustment factor. The PEA can then be interpreted in the same way as the regression coefficients from an OLS regression (Wooldridge, 2012):

$$\mathbf{PEA} = \boldsymbol{\Phi}\left(\frac{\overline{\mathbf{X}}\hat{\boldsymbol{\beta}}}{\hat{\boldsymbol{\sigma}}}\right) \tag{11}$$

As a second step, we control our results for the existence of spatial interdependence. Basically, spatial interdependence can be introduced into a regression model either through global or local spillover effects. The latter are present if a change in the characteristics $\mathbf{X}$ of neighbouring observations $\mathbf{j}$ affects the outcome $\mathbf{Y}$ of an observation $\mathbf{i}$. Global spillover effects, on the other hand, imply that a change in a characteristic or outcome of one observation affects not only the outcome of neighbouring observations, but also has the effect of passing like a wave through all observations in the sample, ultimately leading to endogenous feedback effects (LeSage, 2014). In the case of an emerging alternative crop, the adoption as well as the characteristics of neighbouring observations $\mathbf{j}$, for example a shared resource, could influence the adoption of an observation $\mathbf{i}$.

Because of the interesting notion of feedback effects, most applied empirical work focuses on global spillover effects. It has become common practice in applied econometrics (see e.g. Anselin, 2010; or for an overview Pinkse and Slade, 2010) and also in an agricultural context

(Anselin et al., 2004; Gellrich and Zimmermann, 2007; Holloway et al., 2007; Roe et al., 2002; Schmidtner et al., 2012) to carry out tests for spatial autocorrelation and adapt standard regression models to model spatial effects. However, this procedure has recently been subject to growing criticism. Specifically, Gibbons and Overman (2012) argue that most applied spatial econometric research is plagued by identification problems of the causal relationships at work and, in addition, it focuses too much on statistical tests when determining the appropriate model specification. Instead of the predominantly used spatial autoregressive (SAR) model, which estimates global spillover effects, they advocate the use of the simpler Spatial Lag of X (SLX) model, first introduced by LeSage (2009), which estimates local spillover effects, and they call for more focus on theoretical considerations and the precise formulation of research questions when analysing spatial interdependence[16]. In response, Halleck Vega and Elhorst (2015) also advocate the SLX model as a point of departure when controlling for spatial interdependence. We follow the approach proposed by Halleck Vega and Elhorst (2015) and estimate a SLX Tobit model which takes on the form

$$\mathbf{Y}^* = \boldsymbol{\alpha}\boldsymbol{\iota}_{\mathbf{N}} + \mathbf{X}\boldsymbol{\beta} + \mathbf{W}\mathbf{X}\boldsymbol{\gamma} + \mathbf{u}, \tag{12}$$

where $\mathbf{W}$ is a neighbourhood matrix with the dimensions $\mathbf{N} \times \mathbf{N}$ which is often based on continuous neighbourhood if the observations are administrative units (e.g. municipalities which share common boundaries). In such a continuous neighbourhood matrix, observations which share a border are neighbours and receive the value 1 and all other observations receive the value 0. Moreover, an observation cannot be a neighbour of itself and therefore the diagonal elements of $\mathbf{W}$ are also 0. Before estimation of the model, $\mathbf{W}$ has to be row standardised, so that all rows sum up to unity. The result of the multiplication of $\mathbf{W}$ with $\mathbf{X}$ is a spatial lag variable $\mathbf{WX}$, which represents for every observation the average values of the independent variables of its respective neighbours. In the SLX model, the PEA of $\boldsymbol{\beta}$ measures the direct effects of $\mathbf{X}$ on $\mathbf{Y}$, while the PEA of $\boldsymbol{\gamma}$ measures local spillover effects of $\mathbf{WX}$ on $\mathbf{Y}$. If the PEA of $\boldsymbol{\gamma}$ is statistically significant, local spatial interdependence is present. This offers a very flexible way of modelling spillovers, as spillover effects may differ for every independent variable to an extent that they can even take on different signs. In contrast, in the SAR model the ratio between direct and spillover effects is constant for all variables and the spillover effects always have the

[16] For a more detailed line of argument, please refer to (Gibbons and Overman, 2012; and Halleck Vega and Elhorst, 2015).

same sign as direct effects, which is a rather restrictive and undesirable property (Pace and Zhu, 2012).

To test the robustness of our model specification, we estimate all SLX Tobit models with two different neighbourhood matrices, namely one based on continuous neighbourhood and one based on a cut-off distance of 10 kilometres (Euclidean distance between geographic centroid points of municipalities), where neighbours are additionally weighted according to their inverse distance. The decision on the cut-off distance is based on expert knowledge regarding the structure of the oil pumpkin market in Austria and on comparison with other work which analyses spatial interdependencies in agriculture (Schmidtner et al., 2015).

2.3 Case study and empirical application

2.3.1 The Styrian Oil Pumpkin

The Styrian Oil Pumpkin (*Cucurbita pepo subsp. Pepo var. Styriaca*) is a variety within the subspecies *Cucurbita pepo subsp. pepo*. It emerged in the Austrian federal state of Styria in the first half of the 19th century due to a spontaneous mutation, which led to the loss of the outer hull of its seeds, facilitating oil production and giving the oil a very distinct dark green colour and a nut-like taste (Fruhwirth and Hermetter, 2007). In contrast to other pumpkin varieties, it is therefore considered an oilseed crop. The average yield of pumpkin seeds is about 500-600 kg/ha, but it is very sensitive to weather conditions and can range from 400kg/ha up to 1,000 kg/ha. The highest quality seeds are sold as a salty or sweet snack, but most are processed in oil mills to make pumpkin seed oil (Cretnik, 2015). About 2.5 kg of pumpkin seeds are required to produce one litre of pumpkin seed oil (Fruhwirth and Hermetter, 2007).

The cultivation of Styrian Oil Pumpkin in Austria has a long tradition in the federal state of Styria and the neighbouring southern part of Burgenland. However, since the 1970s it has also received increasing attention in parts of Lower Austria. Since 1996 the name Styrian Pumpkin Seed Oil is registered as a PGI (European Union, 1995) and therefore protected within the EU quality schemes for agricultural products and foodstuffs based on the EEC Regulation 2081/92, currently regulated by EEC Regulation 1151/2012 (European Union, 2012). Within this framework, a product may be registered under one of two labels, PGI or Protected Designation of Origin (PDO), to protect the name of the geographical region which a product bears. However, to be registered as a PGI or PDO, the product requires a link to the geographical region and has to be produced according to individually defined production standards regarding ingredients and production method (Becker, 2009). The PGI for Styrian Pumpkin Seed Oil is administered at the national level by the Styrian Pumpkin Seed Oil PGI Community Association, which has about 3,000 members (2,500 farmers and 50 oil millers). When farmers and/or oil millers become members of the Styrian Pumpkin Seed Oil PGI Community Association, they have to comply with production standards, which are monitored regularly by an external control authority (Cretnik, 2014). Styrian Pumpkin Seed Oil PGI may only be produced from Styrian Oil Pumpkins cultivated in the south-eastern part of Styria, the southern part of Burgenland and two regions in Lower Austria (see Figure 2). The processing of the seeds into oil is limited to the parts of Styria and Burgenland within this area and has to be carried out using a defined production method (European Union, 1995). Therefore, PGI seeds from the northern part of the PGI area have to be transported to oil mills in the southern part for the production of Styrian Pumpkin Seed Oil PGI. Even though this step in the production process is associated with additional transport costs, they are of minor importance, as the monetary value per unit of transported weight is, with approximately €4/kg oil pumpkin seeds, relatively high (Styrian Chamber of Agriculture, 2015).

The definition of the PGI area may be different than one would expect, as the name of the product intuitively suggests Styria as the protected geographical area. Before its registration, two separate groups, namely (i) farmers and (ii) oil millers, applied for a geographical indication for Styrian Pumpkin Seed Oil. Farmers, aiming for high and stable prices, wanted a PDO which limited the cultivation of Styrian Oil Pumpkins and the processing of seeds into oil to Styria. Oil millers, having the production of large quantities of pumpkin seed oil in mind, were aiming for a PGI with cultivation limited to Austria and processing limited to Styria. Eventually, both sides, trying to make sure their interests prevailed, came to a compromise in the form of the resulting definition, as only one geographical indication may be registered for a product (Brandstetter, 2014; Cretnik, 2014).

Since the registration of the PGI in 1996, the cultivation of oil pumpkin in Austria has undergone a dynamic development. Driven by an increasing demand for products from the Styrian Oil Pumpkin, many farmers began to cultivate it or extended their acreage, leading to an increase in oil-pumpkin planted area from about 9,000 ha in 1995 to approximately 9,800 ha in 2000, 16,000 ha in 2006, 24,000 ha in 2010 and 32,000 ha in 2015. The farmers who produce Styrian Oil Pumpkins according to the specification of the PGI are able to achieve a price premium. For example, in 2015 the price for PGI seeds was approximately €4/kg, while for non-PGI seeds it was about €3,70/kg (Styrian Chamber of Agriculture, 2015). Therefore, the vast majority of oil pumpkin (roughly 90 per cent) is cultivated in the PGI area (AMA, 2015), whereas oil-pumpkin seeds cultivated outside the PGI area are mainly used for seed propagation (Brandstetter, 2013).

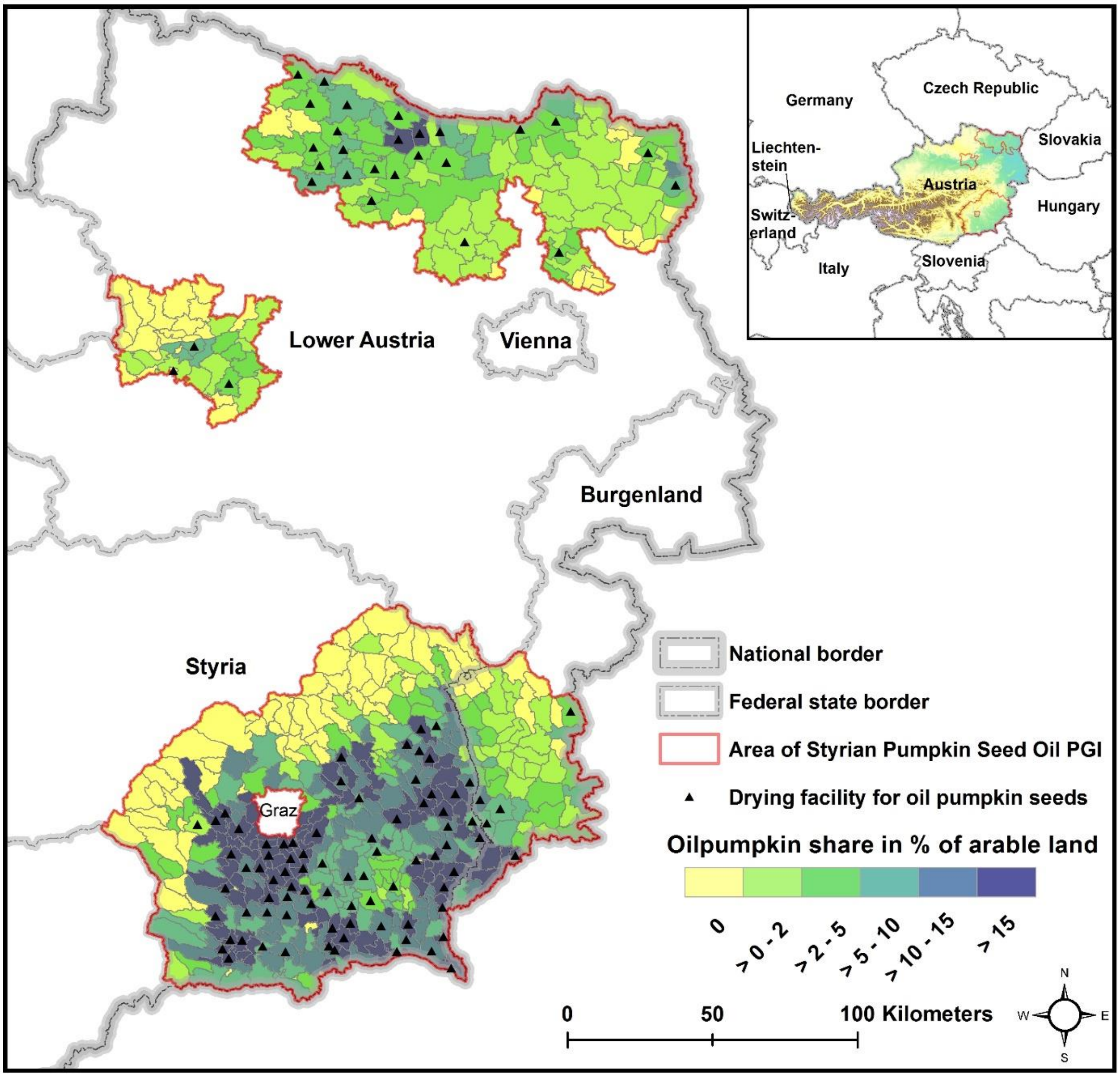

Figure 2. Oil-pumpkin cultivation in municipalities located in the PGI area for Styrian Oil Pumpkin in 2010

Source: (Own representation with data from: Basemap, s.a.; BMLFUW, 2013, 2014; EuroGraphics, s.a.; Statistik Austria, 2013; Styrian Pumpkin Seed Oil Community Association, 2015)

Between 2000 and 2014, oil-pumpkin cultivation within the PGI area increased in the northern part from 1,700 to 8,200 ha (+380%) and in the southern part from 8,500 to 13,700 ha (+60%) (Statistik Austria, 2015), illustrating different regional dynamics in the expansion of oil-pumpkin planted area. The potential for oil-pumpkin cultivation in these areas, considering crop-rotation limitations, are 65,000 ha and 16,000 ha, respectively (Cretnik, 2014)[17]. Therefore, especially the northern part of the PGI area still has a great potential for a further increase in oil-pumpkin planted area.

2.3.2 Data basis and derivation of model variables

For the empirical models, we combine various data sources. Data on farm characteristics, crop cultivation and livestock is acquired from the municipality database (GEDABA) from the Austrian Federal Ministry of Agriculture, Forestry, Environment and Water Management (BMLFUW, 2013). The Integrated Administration and Control System (IACS) database provides data on the biophysical quality of agricultural land and subsidies (BMLFUW, 2014). Socio-economic data on farms and farm holders is taken from the farm census (Statistik Austria, 2013). The Styrian Pumpkin Seed Oil Community Association provided us with data on the locations of washing and drying facilities (Styrian Pumpkin Seed Oil Community Association, 2015).

In comparative studies, the spatial scale of analysis is either at the level of farms (e.g. Jensen et al., 2007) or administrative units (e.g. Consmüller et al., 2010). We carry out the analysis at the level of municipalities, which is the smallest level of aggregation available. In the literature, analyses are often carried out at the municipality level (e.g. Viaggi et al., 2015), as data is mostly available and still offers a spatial resolution that is fine enough to identify local heterogeneity of observations. We use cross-sectional data from the year 2010 of the 563 municipalities located in the Styrian Pumpkin Seed Oil PGI area, because a full farm census is only carried out every 10 years, with the most recent data being from 2010. Before estimation of the models, several observations are removed from the dataset, to reduce the effect of outliers and very small municipalities in terms of arable land (less than 5 ha). After this step, 549 municipalities remain and represent the basis for our further analysis.

We now develop an overview of factors which may influence the spatial variations in oil pumpkin cultivated area within the PGI area for Styrian Pumpkin Seed Oil. We define the share of arable land cultivated with oil pumpkin *(oilp)* as the dependent variable. In crop production, different crops compete for a finite area of arable land. The share of arable land cultivated with a specific crop should therefore reflect its relative profitability, compared to other crops (Garrett

[17] According to Heyland et al. (2006), the share of oil pumpkin within crop rotation should not exceed 25 per cent due to phytopathological aspects.

et al., 2013) and, to a certain extent, also to livestock production (depending on the area of arable land which is required for the production of fodder). We hypothesise that the relative profitability of oil-pumpkin production, compared to competing crops in a cross-sectional setting with fixed price differences, depends on *the natural quality of arable land* and access to *special machinery* required for oil-pumpkin production, as well as *production-, marketing-, and policy*-related, *social, temporal, regional* and *spatial* factors. To limit the discussion on the broad range of possible factors, we focus on variables which are available for our analysis.

The *natural quality of arable land* influences the yield potential. Moreover, pumpkins are not frost-tolerant and therefore require favourable climatic conditions during their vegetative period from April to September (Diepenbrock et al., 1999). We therefore introduce the soil quality index of arable land *(soilqual)* as our first independent variable. It is an index number which ranges from 0 to 100 and describes the quality of arable land, considering soil quality, climatic conditions and topography.

While the cultivation of oil pumpkins can be carried out with a precision drill, which, for example, is also used for maize, other steps in the production process require *special machinery*. Pumpkin seed harvesters pick up and crush the pumpkins and collect the seeds (Heyland et al., 2006). After harvesting, the seeds have to be washed and dried within a relatively short time frame (approximately 6 hours) in stationary washing and drying facilities (Cretnik, 2015). Proximity to a washing and drying facility for pumpkin seeds is therefore considered another prerequisite for oil-pumpkin cultivation and is introduced in our analysis with the variable *distdry*, which indicates the distance from the nearest washing and drying facility in kilometres (Euclidean distance between geographical centroid points of municipalities). As the machinery required for the harvest as well as for washing and drying of the seeds is relatively expensive, these steps in the production process are often carried out by agricultural service companies or organised collaboratively via agricultural communities (Brandstetter, 2014). We therefore include the variable *agriserv*, which indicates the amount of agricultural service provided to farms in working days per farm.

Another important aspect is the *production* and *marketing* structure. The southern part of the PGI area is characterised by a very long tradition in oil-pumpkin cultivation, small farms and a high proportion of direct-marketing farms (Cretnik, 2014). In the northern part, farms are larger and oil-pumpkin cultivation also has a certain tradition, but it is not so important for regional identity and therefore the direct marketing of pumpkin-seed products is also less prevalent. In addition, farms are larger in terms of utilised agricultural area (UAA). Nevertheless, especially in the northern PGI area the oil pumpkin is an interesting crop for organic farms (Brandstetter, 2014). Oil pumpkins are well suited to organic farming, since after harvesting of the pumpkin seeds, the pulp mostly remains on the field and provides nutrients for subsequent crops (Heyland et al., 2006). Moreover, a special product line, "Organic Styrian Pumpkin Seed Oil PGI", guarantees organic farms an additional price premium. Farm size may have a negative or positive effect on oil-pumpkin cultivation. Due to their limited area of arable land, small and medium-sized farms have to focus on more labour-intensive crops with higher gross margins per hectare, for example oil pumpkins, and/or on alternative forms of production/marketing of their products in order to achieve an appropriate farm income. This is more difficult for larger farms, where labour constraints often occur. However, according to the literature, larger farms tend to possess the financial capacities to invest in special machinery and may also benefit from economies of scale (Garrett et al., 2013). To control for the effect of farm size in our model, we include the variable *farmsize*, measured as ha of UAA per farm. The next variable – share of organic farms per municipality (*organic*) – should reflect the above mentioned differing production and marketing conditions of organic farms. To consider the different marketing possibilities of direct marketing farms, we include their share compared to that of all farms (*dirmark*). The competition from livestock production for arable land is considered with the variable livestock, measured in livestock units per ha UAA.

Subsidies may be a *policy*-related factor which influences spatial variations in oil-pumpkin cultivation. The UBAG[18] subsidy, for example, was granted for extensive land-use practices on arable land and grassland within the previous Austrian agri-environmental programme. For arable land, these practices included, for example, a wider crop rotation (less than 75% cereals and maize) and low fertiliser input (BMLFUW, 2015). Therefore, this subsidy may have been an incentive for farmers to cultivate oil pumpkin in order to widen their crop rotation. We control for an effect of this subsidy with the variable *ubagarable*, which measures the sum of UBAG subsidy in €, granted for arable land per municipality.

In terms of *social* factors, the responsiveness of farmers to the dynamic development of oil pumpkin cultivation in recent years may be relevant in explaining spatial variations in oil pumpkin planted area. The literature shows that farmer characteristics such as age or level of education and the social environment often play a role in this context (e.g. Knowler and Bradshaw, 2007; Läpple et al., 2015). For our analysis, data on the level of education of farmers

[18] UBAG is an abbreviation for the environmentally friendly management of arable land and grassland.

is available, which we consider with the variable *education*, describing the share of farmers with a higher agricultural education. Within the farm census, this is defined as an agricultural education which comprises at least three years (Statistik Austria, 2013).

Finally, *temporal* as well as *regional* aspects and spatial interdependence may also play a crucial role. Historical factors such as a longer tradition in oil-pumpkin cultivation are likely to have caused current differences in oil-pumpkin shares. To consider such unobserved heterogeneity among municipalities in a cross-sectional analysis with aggregated data, a temporal lag of the dependent variable (the mean of the oil-pumpkin shares from 2000 and 2001[19]) is included as a control (*oilplag*) – a procedure proposed by Wooldridge (2012). Another control variable which we include is the total area of arable land per municipality (*arable*). As the dependent variable is defined as the share of oil-pumpkin cultivated area of total arable land, it depends on both, the oil-pumpkin cultivated area and the total arable land per municipality. It is, for example, possible that oil-pumpkin shares are related to the size of municipalities in terms of arable land. Not considering such an effect would therefore cause a bias, when estimating marginal effects (Viaggi et al., 2015). Including the total arable land per municipality as an independent variable allows us to control for a separate size effect on oil pumpkin shares and thus to estimate the effects of other independent variables in a scale neutral manner, independent of the size of a municipality in terms of arable land (Wooldridge, 2012). Since we suspect that the effects of the independent variables differ among regions, including regional dummy variables is not sufficient. Therefore, we estimate separate regression models for the northern and southern PGI area, which allows us to identify region-specific effects for the independent variables (Wooldridge, 2012). With regard to spatial interdependence, it is possible that, for example, a well-established marketing infrastructure for oil-pumpkin products or the co-operative use of machinery in neighbouring municipalities **j** have a positive influence on the oil-pumpkin planted area in a municipality **i**. To control for such local spatial interdependencies, we add spatial lags of the independent variables to our model. However, we only include spatial lags of the variables *dirmark*, *organic*, *agriserv* and *education*. The two variables *arable* and *oilplag* are not included as spatial lags because they serve primarily as control variables and therefore it is of no interest to interpret their marginal effects. For the other independent variables no spatial lags are estimated, because the high correlation with their

[19] The years 2000 and 2001 represent the earliest data available for our analysis and we therefore consider them to be the most suitable in reflecting the historical factors which influence oil-pumpkin cultivation.

spatial lags does not allow us to identify their marginal effects[20]. As a final measure, we apply the natural logarithm to the variables *farmsize*, *ubagarable* and *arable* to approximate a normal distribution and reduce the effect of outliers (Wooldridge, 2012).

Table 2 gives an overview of the variables used in our regression models. Means and standard deviations of model variables for both regions (the northern and southern PGI area) are provided. Alongside the description of the independent variables, we also include the expected signs of the independent variables. A major pattern which can be observed is that the mean values of most variables vary considerably between the two regions, illustrating the different regional preconditions for oil-pumpkin cultivation.

Table 2. Descriptive statistics

Category	Variable (Hypothesised sign)	Expe-cted sign	Code	Northern PGI area (n = 143)	Southern PGI area (n = 406)	Unit
Dependent variable	Share of oil pumpkin in per cent of arable land		*oilp*	2.31 (3.25)	10.68 (9.31)	%
Natural	Soil-quality index of arable land	+	*soilqual*	51.48 (10.11)	42.51 (7.77)	index (0-100)
Machinery	Distance from nearest washing/drying facility	-	*distdry*	3.95 (3.72)	4.20 (5.03)	km
Machinery	Agricultural service per farm	+	*agriserv*	1.00 (1.28)	0.80 (1.10)	days/farm
Production	Farm size	+/-	*farmsize*	36.16 (17.53)	12.74 (7.84)	ha UAA
Production	Share of organic farms	+	*organic*	11.80 (11.29)	8.98 (8.31)	%
Production	Livestock density	-	*livestock*	0.38 (0.46)	0.99 (0.52)	LU/ha UAA
Marketing	Share of farms with direct marketing	+	*dirmark*	4.46 (3.86)	7.47 (5.93)	%
Policy	UBAG subsidy for arable land	+	*ubagarable*	120,150.32 (116,241.32)	13,671.75 (2,892.26)	€
Social	Share of farmers with higher agricultural education	+	*education*	33.89 (11.87)	17.06 (8.97)	%
Temporal (control)	Temporal lag of oil-pumpkin share (mean of 2000 and 2001)	+	*oilplag*	0.64 (1.75)	5.37 (5.86)	%
Size (control)	Arable land	+	*arable*	1.928.59 (1.532.81)	413.08 (396.14)	ha

Note: Means and standard deviations in parenthesis; LU = livestock unit; UAA = utilised agricultural area
Source: Various sources given in the text.

[20] A similar problem occurred in the study of Storm et al. (2015), which also led them to exclude certain spatial lag variables from their analysis.

2.4 Results

For each of the two regions within the PGI area, a Tobit and SLX Tobit model were calculated, which leads to a total of four models. The results of the estimated regression models are provided in Table 3. To enable direct interpreting of the effects of the independent variables on the share of arable land cultivated with oil pumpkin, the PEAs are presented instead of the estimated coefficients[21]. Overall, most signs of the PEAs are in line with the hypothesised direction of their effect on the share of arable land cultivated with oil pumpkin. With regard to the spatial models, the results of the two SLX models do not differ substantially from the two Tobit models. We therefore focus mainly on the PEAs of the Tobit model for an interpretation of the results and we only refer to the PEAs of the SLX Tobit model when differences arise. With respect to the neighbourhood matrices it should be pointed out that we only present the results based on the continuous neighbourhood matrix and relegate the results based on the distance-based neighbourhood matrix to the Appendix, as they do not differ substantially[22].

In the model for the northern PGI area, the coefficient of the soil-quality index (*soilqual*) indicates a weak positive connection of the natural quality of arable land with oil-pumpkin shares, which is however only significant at the 10% level. As expected, we find a negative relationship between the distance from the nearest washing and drying facility (*distdry*) and oil-pumpkin shares. One additional kilometre to the nearest washing and drying facility leads on average to a decrease in oil-pumpkin cultivation of 0.25 percentage points. On the contrary, the days of agricultural service provided to farms (*agriserv*) are not significant.

For the production-related factors, we find a weak, negative PEA for *farmsize* which is significant at the 10% level. As for the other log-transformed independent variables, a change of $\mathbf{x_k}$ by 1% can be interpreted as a percentage-point change of $\mathbf{Y}$. An increase in farm size by 1% therefore is associated with a decrease in oil-pumpkin share of 0.01 percentage points. The next variable, *organic*, represents the different production and marketing conditions of organic farms. An increase in the share of organic farms of one percentage point is associated with an increase in oil-pumpkin share of 0.09 percentage points. Hence, organic farming, holding other

---

[21] Detailed results of the four models can be found in the Appendix.

[22] Even though it is a common belief that model results are sensitive to the specification of W, LeSage and Pace (2014) demonstrate that different specifications of $\mathbf{W}$ in general do not lead to substantially different inferences, if the marginal effects are interpreted correctly.

factors fixed, has a statistically significant (1% level) and positive relationship with oil-pumpkin shares. On the contrary, the variable livestock is not significant.

For the share of farms with direct marketing (*dirmark*), surprisingly we find a weak negative relationship with oil-pumpkin shares (0.07) which is, however, only significant at the 10% level. *Education* has a weak positive connection with oil-pumpkin shares. However, the PEA (0.03) is only statistically significant at the 10% level in the SLX Tobit model. Not surprisingly, the temporal lag of historical oil-pumpkin shares (*oilplag*) has a strong positive effect which is significant at the 1% level. If the historical oil-pumpkin share of a municipality is one percentage point higher, the estimated oil-pumpkin share is 1.05 percentage points higher. However, the primary purpose of this variable is not to interpret its PEA, but rather to control for historical factors which are responsible for current differences in oil-pumpkin shares and which could not otherwise be accounted for in the analysis. Finally, none of the spatial-lag variables in the SLX Tobit model is statistically significant, which means that no local spillover effects are present in the northern PGI area.

Table 3. Partial effects at the average of Tobit and SLX Tobit models for the northern and southern PGI area

Dependent Variable = share of arable land cultivated with oil pumpkin				
	Northern PGI area (n =143) 25% zeroes in dependent variable		Southern PGI area (n = 406) 14% zeroes in dependent variable	
PEA of independent variables	Tobit	SLX Tobit	Tobit	SLX Tobit
Direct effects:				
soilqual	0.04*	0.05*	0.32***	0.32***
distdry	-0.25***	-0.26***	-0.52***	-0.48***
agriserv	0.10 n.s.	0.09 n.s.	-0.02 n.s.	-0.03 n.s.
Log *(farm size)*	-0.01*	-0.01**	-0.03***	-0.03***
organic	0.09***	0.09***	0.02 n.s.	0.02 n.s.
livestock	-0.08 n.s.	-0.07 n.s.	-0.24***	-0.26***
dirmark	-0.07*	-0.07*	0.17***	0.13***
Log (*ubagarable*)	0.002 n.s.	0.003 n.s.	0.003**	0.002 n.s.
education	0.02 n.s.	0.03*	-0.01 n.s.	-0.01 n.s.
oilplag	1.05***	1.04***	0.82***	0.78***
Log (*arable*)	0.0006 n.s.	0.0001 n.s.	-0.002 n.s.	-0.001 n.s.
Local spillover effects:				
W.*agriserv*		0.10 n.s.		-0.11 n.s.
W.*organic*		-0.01 n.s.		0.02 n.s.
W.*dirmark*		-0.10 n.s.		0.26***
W.*education*		-0.02 n.s.		-0.01 n.s.

*Note: the PEAs of the three log-transformed independent variables have been divided by 100 so that a change of x_k by 1% can be interpreted as a percentage-point change of Y; spatial-lag variables are denoted by the prefix "W."; ***, ** and * and denote significance at the 1%, 5% and 10% levels, respectively; n.s. = not significant.*

For the southern PGI area, the coefficient of the variable *soilqual* is, again, positive but higher and more significant compared to the northern PGI area. The variable *distdry* again shows a negative effect, which is also higher than in the northern PGI area and significant at the 1% level. An increase in the distance from the nearest washing and drying facility by one kilometre is associated with a decrease in oil-pumpkin shares of 0.52 percentage points. As in the northern PGI area, the variable *agriserv* is not significant.

The PEAs of the three production-related independent variables differ to some extent in comparison to the northern PGI area. The effect of *farmsize* is also negative but higher in terms of magnitude (0.03) and statistical significance (at the 1% level). Organic farming (*organic*) has no significant effect, whereas *livestock* has a significant (at the 1% level) and higher effect (-0.24). The variable *livestock* was multiplied by 10 to facilitate the interpretation of its PEA. An increase of 0.1 livestock units per ha UAA is therefore associated with a decrease in oil-pumpkin shares of 0.24 percentage points.

In contrast to the models for the northern PGI area, UBAG payments for arable land (*ubagarable*) are shown to have a statistically significant effect, even though it is only significant at the 5% level in the Tobit model, not significant in the SLX Tobit model and its magnitude is very small. In the Tobit model, an increase in UBAG payments of 1% is associated with an increase in oil-pumpkin shares of 0.003 percentage points.

Another region-specific aspect is the positive (0.17) and significant (at the 1% level) relationship of direct marketing (*dirmark*) with oil-pumpkin shares. The next independent variable (*education*) has no statistically significant effect on oil-pumpkin shares. As in the northern PGI area, the PEA of the control variable *arable* is also not significant, meaning that oil-pumpkin shares are independent from the actual size of a municipality in terms of arable land. The other control variable, *oilplag*, is, again, positively related to oil-pumpkin shares, but its PEA is smaller compared to the northern PGI area.

Finally, one of the spatial-lag variables in the SLX Tobit model, *W.dirmark*, has a statistically significant effect on oil-pumpkin shares (at the 1% level). An increase in the average direct-marketing share of neighbouring municipalities **j** of one percentage point is therefore associated with an increase in the oil-pumpkin share in a municipality **i** of 0.26 percentage points.

2.5 Discussion

In our analysis we estimate different regression models to analyse the potential drivers of oil-pumpkin cultivation in the Styrian Oil Pumpkin PGI area. To allow for regional differences between the northern and southern part of the PGI area, we separately estimate one Tobit model for each region, using the same set of variables for both models. Additionally, we control our results for the presence of possible local spatial interdependence by estimating a SLX Tobit model, leading to a total of four regression models.

Altogether the results are consistent with our expectations. We detect a positive effect of natural conditions and historical factors, while there is a negative effect of distance from the nearest washing and drying facility, as well as farm size, on the share of arable land cultivated with oil pumpkin in both regions. The positive effect of natural conditions is plausible and in line with the results of other studies analysing crops with similar climatic requirements, namely soybean and maize (Garrett et al., 2013; Odgaard et al., 2011; Scholz et al., 2013). The higher effect in the southern PGI area is likely attributable to the clearly lower soil-quality indices of municipalities in the alpine foothills west and north of Graz, where climatic, topographic and soil conditions are mostly not suited to oil-pumpkin cultivation.

Also not surprising is the great extent to which historical factors explain spatial variations in oil-pumpkin cultivated area. As Abadi Ghadim et al. (2005) point out, previous experience with a crop has a positive influence on its further adoption. Moreover, including this variable in the analysis allows us to measure the effects of the other independent variables, while holding historical factors – such as a longer tradition or more experience with oil-pumpkin cultivation and other unobserved factors – constant (Wooldridge, 2012). The different magnitude of the effect of the temporal lag of oil-pumpkin shares in the northern and southern PGI area may be explained by the different development of oil-pumpkin cultivation in the two regions since 2000. As oil-pumpkin cultivation has a longer tradition in the southern PGI area and was already very common back in 2000, the further increase in oil pumpkin shares up to 2010 depended less on historical factors (and thus experience) than in the northern PGI area, where growth of oil-pumpkin production is particularly widespread in those municipalities which already had noticeable oil-pumpkin shares in 2000.

As outlined in Section 2.3.2, we find that proximity to a washing and drying facility is a prerequisite for oil-pumpkin cultivation. Pannell et al. (2006) also point out that the compatibility of a new crop with the existing set of technologies, practices and resources on or near a farm facilitates adoption. With regard to farm size, we find that oil-pumpkin shares are on average higher in municipalities with smaller farms, confirming the hypothesis that smaller farms seek more labour-intensive forms of production in order to ensure an appropriate farm income. In the southern PGI area, this effect may be explained by the small average farm size in combination with the high share of direct marketing farms; in contrast, in the northern PGI area, organic farms, which are generally smaller in terms of UAA compared to conventional farms, are more likely to cultivate oil pumpkin.

Besides the above-described overall aspects, we are also able to identify region-specific factors which are related to spatial variations in oil-pumpkin cultivation. The positive effect of organic farming on oil-pumpkin cultivation, which is only significant in the northern PGI area, may be explained by the drier climate in the north-eastern part of Lower Austria, resulting in a lower-yield potential and making organic farming more appealing. Therefore, in 2010 roughly 40% of the oil pumpkins planted in the northern part of the PGI area was cultivated organically, compared to less than 10% in the southern part (Brandstetter, 2014). The negative effect of direct marketing empirically confirms the argument outlined in Section 2.3.2 that direct marketing is of no importance for oil-pumpkin cultivation in the northern PGI area. Farmers in this region, who sell their products via direct marketing, are more likely to focus on the production of other products such as onions or potatoes.

In contrast, in the southern PGI area, direct marketing is identified as an important factor in promoting oil-pumpkin cultivation and organic farming has no significant effect. This result confirms the hypothesis that direct marketing is an important regional sales channel for oil pumpkin products like pumpkin-seed oil or pumpkin-seed snacks. In the literature, direct marketing is also identified as a strategy which can provide particularly smaller farms with a higher financial benefit (Hinrichs, 2000). The regional importance of direct marketing in the southern PGI area may therefore be explained by the smaller farm structure, in combination with the long tradition of – and therefore also strong contribution to – regional identity by the Styrian Oil Pumpkin. Moreover, there seems to be a negative relationship between animal production and oil-pumpkin cultivation in the southern PGI area. This region-specific effect is likely to be based on a different orientation of agricultural production. While farmers in the northern PGI area mainly focus on cash-crop production (average: 0.38 LU/ha UAA), livestock production is of more importance to farmers in the southern PGI area (average: 0.99 LU/ha UAA). The livestock system in the latter area is characterised mainly by pig farming south and east of Graz, while cattle farming is more dominant in the alpine foothills west and north of Graz. However, it cannot be clearly confirmed whether the negative effect of livestock density arises because of competition (e.g. with pig production) or lesser suitability of oil-pumpkin cultivation (a negative correlation of oil-pumpkin shares with grassland shares and cattle production). One reason for the positive effect of UBAG payments could be that farmers in the southern PGI area have a more maize- and cereal-dominated crop rotation and they mostly extended their production to soybean or oil pumpkin when they participated in the UBAG subsidy. In contrast, farmers in the northern PGI area have a more diverse crop rotation, including, for example sugar beet, sunflower or rape, which also explains the higher UBAG payments received in the northern PGI area, despite the lower oil-pumpkin share.

Finally, higher shares of direct-marketing farms in neighbouring municipalities **j** are positively connected to the oil-pumpkin share in a municipality **i**. This local spatial interdependence may have several meanings. First of all, more direct marketing in neighbouring municipalities could attract more potential customers and could therefore lead to an increase in oil-pumpkin cultivation. Secondly, it is possible that farmers, who have no direct marketing, sell their products to nearby direct-marketing farmers, which would also lead to local spatial interdependence. A third possible reason concerns the issue of cause and effect in a regression analysis. It is also possible that the positive PEA of the variable *W.dirmark* simply describes the correlation of neighbouring direct-marketing shares with oil-pumpkin shares and no partial effect. It might, for example, be that direct-marketing shares in municipalities depend on the distance from the nearest big city and therefore higher direct-marketing shares of neighbouring municipalities would rather reflect their shared proximity to a city instead of a local spillover effect. As also stated in Storm et al. (2015), it is therefore not possible to assess empirically through which of the above described channels the spatial effects arise.

From a methodological perspective, due to lack of data, our analysis is limited to the municipality level. This may lead to the ecological fallacy problem (Anselin, 2002) and the modifiable areal unit problem (Openshaw, 1984), meaning that results from (artificially) aggregated data may be different or even the reverse, compared to the level at which economic agents (farmers) act. In a spatial econometric context, the aggregation of data may also lead to artificial spatial effects. Even though Schmidtner et al. (2015) show that previously found evidence for spatial effects in organic farming in Germany at the county level is also relevant at the municipality level, these aspects have to be considered, when interpreting our results. Our decision to use aggregated data for the whole PGI area instead of, for example, carrying out a survey for a sample of the whole farm population, enabled us on the one hand to examine the influence of spatial interdependence on spatial variations of oil-pumpkin cultivated area; on the other hand, this approach also prevented us from considering the risk-preferences and risk-perceptions of farmers which are also likely to influence their decision to cultivate oil pumpkin in our models (Abadi Ghadim and Pannell, 1999). Finally, our results are only valid for a given point in time (the year 2010) and therefore do not reflect the temporal dynamics of oil-pumpkin cultivation. Nevertheless, our approach allows us to identify the causes of regional patterns in oil-pumpkin cultivated areas which are crucial for a better understanding of the adoption and expansion of the Styrian Oil Pumpkin.

2.6 Conclusions

While other studies focus more on the decision process of individual farmers in adopting a new crop or production system, our study analyses the causes of spatial variations in oil-pumpkin cultivated area on an aggregated scale, emphasising regional heterogeneity and spatial interdependence. The results of our analysis show that, apart from overall basic prerequisites like favourable natural conditions, the proximity to washing and drying facilities for pumpkin seeds and previous experience with oil-pumpkin cultivation, the spatial variations of oil-pumpkin cultivated areas also depend on region-specific production and marketing structures (organic farming in the northern part of the PGI area, direct marketing in the southern part of the PGI area), as well as possible interdependence between neighbouring municipalities which may lead to positive externalities (local spatial spillover effect of direct marketing in the southern part of the PGI area).

The conclusions which can be drawn from these results not only apply to oil-pumpkin cultivation, but also, at a more general level, to other emerging products or production systems in agriculture. They reveal that, besides (i) product or production system-specific, also (ii) region-specific and (iii) spatial aspects need to be considered for the design of policies aimed at facilitating their adoption and further extension. In general, our results emphasise the importance of providing the necessary framework conditions for the success of an alternative crop or production system. These include not only infrastructure, which is of particular importance for crops and production systems with high transaction costs, as well as expertise with respect to the product or production system, but also a functioning supply chain with up- and downstream operators (Allaire et al., 2015). The question is whether or not existing policy measures within the current CAP, which are very often based on field subsidies, are suited to the provision of these framework conditions. Moreover, if regional differences in the effects of drivers influencing the adoption of a new crop or production system are ignored, the results may lead to misleading implications for the whole population which, in fact, only apply to one region within this population. For our case study this means that policy measures aimed at supporting the direct marketing of oil-pumpkin products seem promising in the southern PGI area and may also be able to exploit positive externalities in areas with a high concentration of direct-marketing farms, whereas in the northern PGI area the promotion of organic oil-pumpkin cultivation is a possible option. Furthermore, the creation of additional washing and drying facilities should be facilitated particularly in the northern PGI area, where the further potential for oil-pumpkin cultivation is still greater. However, such policies need to consider the location and capacities of existing infrastructure as well as the further development of the oil-pumpkin market.

With respect to spatial interdependence as a source of spatial variations in the adoption of a new crop or production system, we find that ignoring spatial dependence does not lead to a substantial bias of model results in our case. Nevertheless, we recommend to control the results for spatial interdependence if there is a convincing theoretical argument which supports the possible presence of spatial interdependence. However, we would also point out that more attention should be payed to the selection of the appropriate spillover specification (local or global spillover) and to the critical interpretation of spatial effects.

One remaining shortcoming is the spatial and temporal resolution of our analysis. An analysis with farm-level panel data would help us to better understand the individual decision processes, as well as their spatio-temporal dynamics, and could thus provide policy makers with more detailed information. If suitable panel data at farm level is available in the future, such an analysis will be a possible avenue for further research.

2.7 Appendix

Table 4. Estimation results of the Tobit model for the northern PGI area

Independent Variable	Coefficient	Std. error	z-value	Pr. z
intercept	-1.3233	2.6714	-0.4953	0.6204
soilqual	0.0509	0.0263	1.935	0.0530
distdry	-0.3044	0.0566	-5.3772	0.0000
agriserv	0.1140	0.1245	0.9156	0.3599
log(*farmsize*)	-1.2121	0.6198	-1.9554	0.0505
organic	0.1088	0.0172	6.3118	0.0000
livestock	-0.0998	0.0709	-1.4077	0.1592
dirmark	-0.0893	0.0454	-1.9683	0.0490
log (*ubagarable*)	0.2934	0.2755	1.0648	0.2870
education	0.0241	0.0171	1.4083	0.1590
oilplag	1.2568	0.0955	13.1638	0.0000
log (*arable*)	0.0671	0.4567	0.1470	0.8831

Dependent variable = share of arable land cultivated with oil pumpkin; Spatial- lag variables are denoted by the prefix "W.".

Table 5. Estimation results of the Tobit model for the southern PGI area

Independent Variable	Coefficient	Std. error	z-value	Pr. z
intercept	2.0617	2.8433	0.7251	0.4684
soilqual	0.3230	0.0503	6.4228	0.0000
distdry	-0.5317	0.0913	-5.8252	0.0000
agriserv	-0.0160	0.2521	-0.0635	0.9494
log (*farm size*)	-3.1970	0.8262	-3.8697	0.0001
organic	0.0200	0.0395	0.5075	0.6118
livestock	-0.2543	0.0604	-4.2139	0.0000
dirmark	0.1711	0.0512	3.3407	0.0008
log (*ubagarable*)	0.2771	0.1383	2.0035	0.0451
education	-0.0109	0.0336	-0.3238	0.7461
oilplag	0.8495	0.0600	14.1534	0.0000
log (*arable*)	-0.2440	0.3265	-0.7474	0.4548

Dependent variable = share of arable land cultivated with oil pumpkin; Spatial- lag variables are denoted by the prefix "W.".

Table 6. Estimation results of the SLX Tobit model for the northern PGI area with W based on continuous neighbourhood

Independent Variable	Coefficient	Std. error	z-value	Pr. z
intercept	-0.1796	2.8905	-0.0621	0.9505
soilqual	0.0565	0.0299	1.8923	0.0585
distdry	-0.3057	0.0573	-5.3364	0.0000
agriserv	-0.0875	0.0720	-1.2142	0.2247
log (*farmsize*)	-1.2299	0.6107	-2.0140	0.0440
organic	0.3057	0.2789	1.0961	0.2730
livestock	0.0060	0.4577	0.0132	0.9895
dirmark	1.2328	0.0959	12.8548	0.0000
log (*ubagarable*)	-0.0853	0.0467	-1.8256	0.0679
education	0.1088	0.0186	5.8401	0.0000
oilplag	0.1097	0.1223	0.8968	0.3698
log (*arable*)	0.0316	0.0173	1.8326	0.0669
W.agriserv	-0.1206	0.0793	-1.5212	0.1282
W.organic	-0.0106	0.0326	-0.3240	0.7460
W.dirmark	0.1230	0.2414	0.5095	0.6104
W.education	-0.0228	0.0285	-0.8000	0.4237

Dependent variable = share of arable land cultivated with oil pumpkin; Spatial- lag variables are denoted by the prefix "W.".

Table 7. Estimation results of the SLX Tobit model for the northern PGI area with W based on a cut-off distance of 10km and weights based on inverse distance

Independent Variable	Coefficient	Std. error	z-value	Pr. z
intercept	0.4454	2.8812	0.1546	0.8771
soilqual	0.0567	0.0301	1.8846	0.0595
distdry	-0.3077	0.0565	-5.4444	0.0000
agriserv	-0.0777	0.0718	-1.0825	0.2790
log (*farmsize*)	-1.2595	0.5998	-2.1001	0.0357
organic	0.2580	0.2663	0.9689	0.3326
livestock	0.0634	0.4436	0.1429	0.8863
dirmark	1.2075	0.0954	12.6600	0.0000
log (*ubagarable*)	-0.0886	0.0462	-1.9184	0.0551
education	0.1082	0.0183	5.9247	0.0000
oilplag	0.1196	0.1204	0.9934	0.3205
log (*arable*)	0.0367	0.0172	2.1287	0.0333
W.agriserv	-0.2156	0.0978	-2.2034	0.0276
W.organic	-0.0227	0.0342	-0.6623	0.5078
W.dirmark	0.3206	0.2994	1.0710	0.2842
W.education	-0.0297	0.0303	-0.9814	0.3264

Dependent variable = share of arable land cultivated with oil pumpkin; Spatial- lag variables are denoted by the prefix "W.".

Table 8. Estimation results of the SLX Tobit model for the southern PGI area with W based on continuous neighbourhood

Independent Variable	Coefficient	Std. error	z-value	Pr. z
intercept	0.2418	3.2132	0.0753	0.9400
soilqual	0.3259	0.0512	6.3694	0.0000
distdry	-0.4934	0.0925	-5.3372	0.0000
agriserv	-0.2670	0.0608	-4.3909	0.0000
log (*farmsize*)	-3.3068	0.8670	-3.8142	0.0001
organic	0.2299	0.1421	1.6177	0.1057
livestock	-0.0815	0.3498	-0.2331	0.8157
dirmark	0.8051	0.0625	12.8822	0.0000
log (*ubagarable*)	0.1382	0.0528	2.6182	0.0088
education	0.0219	0.0424	0.5176	0.6048
oilplag	-0.0273	0.2509	-0.1088	0.9133
log (*arable*)	-0.0064	0.0360	-0.1780	0.8587
W.agriserv	0.2660	0.1003	2.6512	0.0080
W.organic	0.0245	0.0730	0.3360	0.7369
W.dirmark	-0.1152	0.5720	-0.2014	0.8404
W.education	-0.0140	0.0626	-0.2230	0.8236

Dependent variable = share of arable land cultivated with oil pumpkin; Spatial- lag variables are denoted by the prefix "W.".

Table 9. Estimation results of the SLX Tobit model for the southern PGI area with W based on a cut-off distance of 10km and weights based on inverse distance

Independent Variable	Coefficient	Std. error	z-value	Pr. z
intercept	-1.089	3.4188	-0.3185	0.7501
soilqual	0.3197	0.0510	6.2729	0.0000
distdry	-0.4336	0.0920	-4.7111	0.0000
agriserv	-0.2962	0.0610	-4.8523	0.0000
log (*farmsize*)	-2.6119	0.8723	-2.9943	0.0028
organic	0.2487	0.1431	1.7380	0.0822
livestock	-0.1479	0.3566	-0.4147	0.6783
dirmark	0.7725	0.0634	12.1840	0.0000
log (*ubagarable*)	0.1293	0.0514	2.5140	0.0119
dducation	0.0508	0.0429	1.1853	0.2359
oilplag	-0.0181	0.2473	-0.0731	0.9417
log (*arable*)	-0.0222	0.0356	-0.6222	0.5338
W.agriserv	0.4619	0.1193	3.8713	0.0001
W.organic	-0.0681	0.0865	-0.7877	0.4309
W.dirmark	-1.4933	0.8321	-1.7946	0.0727
W.education	0.0275	0.0800	0.3436	0.7312

Dependent variable = share of arable land cultivated with oil pumpkin; Spatial- lag variables are denoted by the prefix "W.".

2.8 References

Abadi Ghadim, A.K., Pannell, D.J., 1999. A conceptual framework of adoption of an agricultural innovation. Agricultural Economics 21, 145-154, http://dx.doi.org/10.1016/S0169-5150(99)00023-7.

Abadi Ghadim, A.K., Pannell, D.J., Burton, M.P., 2005. Risk, uncertainty, and learning in adoption of a crop innovation. Agricultural Economics 33, 1-9, http://dx.doi.org/10.1111/j.1574-0862.2005.00433.x.

Allaire, G., Poméon, T., Maigné, E., Cahuzac, E., Simioni, M., Desjeux, Y., 2015. Territorial analysis of the diffusion of organic farming in France: Between heterogeneity and spatial dependence. Ecological Indicators 59, 70-81, http://dx.doi.org/10.1016/j.ecolind.2015.03.009.

AMA, (Agrarmarkt Austria), 2015. Getreideanbauflächen in Österreich 2005-2015.

Anselin, L., 2002. Under the hood: issues in the specification and interpretation of spatial regression models. Agricultural economics 27, 247-267, http://dx.doi.org/10.1111/j.1574-0862.2002.tb00120.x.

Anselin, L., 2010. Thirty years of spatial econometrics. Papers in Regional Science 89, 3-25, http://dx.doi.org/10.1111/j.1435-5957.2010.00279.x.

Anselin, L., Bongiovanni, R., Lowenberg-DeBoer, J., 2004. A Spatial Econometric Approach to the Economics of Site-Specific Nitrogen Management in Corn Production. American Journal of Agricultural Economics 86, 675-687, http://dx.doi.org/10.2307/3697808.

Arslan, A., McCarthy, N., Lipper, L., Asfaw, S., Cattaneo, A., 2014. Adoption and intensity of adoption of conservation farming practices in Zambia. Agriculture, Ecosystems & Environment 187, 72-86, http://dx.doi.org/10.1016/j.agee.2013.08.017.

Bartolini, F., Viaggi, D., 2013. The common agricultural policy and the determinants of changes in EU farm size. Land Use Policy 31, 126-135, http://dx.doi.org/10.1016/j.landusepol.2011.10.007.

Basemap, s.a. Topographic map of Austria, www.basemap.at (02.2016).

Becker, T.C., 2009. European Food Quality Policy: The Importance of Geographical Indications, Organic Certification and Food Quality Assurance Schemes in European Countries. Estey Centre Journal of International Law and Trade Policy 10, http://ideas.repec.org/a/ags/ecjilt/48796.html (08.2015).

BMLFUW, (Federal Ministry of Agriculture, Forestry, Environment and Water Management), 2013. Municipality Database, Unpublished.

BMLFUW, (Federal Ministry of Agriculture, Forestry, Environment and Water Management), 2014. Integrated Administration and Control System Database, Unpublished.

BMLFUW, (Federal Ministry of Agriculture, Forestry, Environment and Water Management), 2015. ÖPUL 2007 Übersicht, https://www.bmlfuw.gv.at/land/laendl_entwicklung/le-07-13/agrar-programm/OEPUL-Uebersicht.html (12.2015).

Boulay, A., Tacconi, L., Kanowski, P., 2012. Drivers of adoption of eucalypt tree farming by smallholders in Thailand. Agroforest Syst 84, 179-189, http://dx.doi.org/10.1007/s10457-011-9451-y.

Brandstetter, A., 2013. Personal communication regarding cultivation and harvest of oil pumpkins and further processing of the seeds.

Brandstetter, A., 2014. Interview about the cultivation of Styrian Oil Pumpkin and the production of Styrian Pumpkin Seed Oil PGI.

Consmüller, N., Beckmann, V., Petrick, M., 2010. An econometric analysis of regional adoption patterns of Bt maize in Germany. Agricultural Economics 41, 275-284, http://dx.doi.org/10.1111/j.1574-0862.2010.00439.x.

Cretnik, A., 2014. Interview about the cultivation of Styrian Oil Pumpkin and the production of Styrian Pumpkin Seed Oil PGI.

Cretnik, A., 2015. Personal comunication regarding harvest, processing and use of oil pumpkin seeds.

Darnhofer, I., Schneeberger, W., Freyer, B., 2005. Converting or not converting to organic farming in Austria: Farmer types and their rationale. Agriculture and Human Values 22, 39-52, http://dx.doi.org/10.1007/s10460-004-7229-9.

Diepenbrock, W., Fischbeck, G., Heyland, K.U., 1999. Spezieller Pflanzenbau. UTB Ulmer, Stuttgart.

EuroGraphics, s.a. Worldwide national borders of 2014, http://ec.europa.eu/eurostat/cache/GISCO/geodatafiles/CNTR_2014_03M.zip (02.2016).

European Union, 1995. Regulation (EEC) No 2081/92, http://ec.europa.eu/agriculture/quality/door/documentDisplay.html?chkDocument=5828_1_en (09.2015).

European Union, 2012. Regulation (EU) No 1151/2012 of the European Parliament and of the Council of 21 November 2012 on quality schemes for agricultural products and foodstuffs, in: Union, E. (Ed.), http://eur-lex.europa.eu/LexUriServ/LexUriServ.do?uri=OJ:L:2012:343:0001:0029:en:PDF (09.2015).

Fruhwirth, G.O., Hermetter, A., 2007. Seeds and oil of the Styrian oil pumpkin: Components and biological activities. European Journal of Lipid Science and Technology 109, 1128-1140, http://dx.doi.org/10.1002/ejlt.200700105.

Garrett, R.D., Lambin, E.F., Naylor, R.L., 2013. Land institutions and supply chain configurations as determinants of soybean planted area and yields in Brazil. Land Use Policy 31, 385-396, http://dx.doi.org/10.1016/j.landusepol.2012.08.002.

Gellrich, M., Zimmermann, N.E., 2007. Investigating the regional-scale pattern of agricultural land abandonment in the Swiss mountains: a spatial statistical modelling approach. Landscape and Urban Planning 79, 65-76, http://dx.doi.org/10.1016/j.landurbplan.2006.03.004.

Gibbons, S., Overman, H.G., 2012. Mostly pointless spatial econometrics? Journal of Regional Science 52, 172-191, http://dx.doi.org/10.1111/j.1467-9787.2012.00760.x.

Halleck Vega, S., Elhorst, J.P., 2015. The SLX model. Journal of Regional Science 55, 339-363, http://dx.doi.org/10.1111/jors.12188.

Heyland, K.U., Hanus, H., Keller, E.R., 2006. Ölfrüchte, Faserpflanzen, Arzneipflanzen und Sonderkulturen. Ulmer.

Hinrichs, C.C., 2000. Embeddedness and local food systems: notes on two types of direct agricultural market. Journal of Rural Studies 16, 295-303, http://dx.doi.org/10.1016/S0743-0167(99)00063-7.

Holloway, G., Lacombe, D., LeSage, J.P., 2007. Spatial Econometric Issues for Bio-Economic and Land-Use Modelling. Journal of Agricultural Economics 58, 549-588, http://dx.doi.org/10.1111/j.1477-9552.2007.00127.x.

Isik, M., 2004. Environmental Regulation and the Spatial Structure of the U.S. Dairy Sector. American Journal of Agricultural Economics 86, 949-962, http://dx.doi.org/10.1111/j.0002-9092.2004.00645.x.

Jensen, K., Clark, C.D., Ellis, P., English, B., Menard, J., Walsh, M., de la Torre Ugarte, D., 2007. Farmer willingness to grow switchgrass for energy production. Biomass and Bioenergy 31, 773-781, http://dx.doi.org/10.1016/j.biombioe.2007.04.002 (2007/12//).

Knowler, D., Bradshaw, B., 2007. Farmers' adoption of conservation agriculture: A review and synthesis of recent research. Food Policy 32, 25-48, http://dx.doi.org/10.1016/j.foodpol.2006.01.003.

Lamarque, P., Lambin, E.F., 2015. The effectiveness of marked-based instruments to foster the conservation of extensive land use: The case of Geographical Indications in the French Alps. Land Use Policy 42, 706-717, http://dx.doi.org/10.1016/j.landusepol.2014.10.009.

Langyintuo, A.S., Mekuria, M., 2008. Assessing the influence of neighborhood effects on the adoption of improved agricultural technologies in developing agriculture. African Journal of Agricultural and Resource Economics 2, 151-169, http://purl.umn.edu/56960 (07.2015).

Läpple, D., Kelley, H., 2015. Spatial dependence in the adoption of organic drystock farming in Ireland. European Review of Agricultural Economics 42, 315-337, http://dx.doi.org/10.1093/erae/jbu024.

Läpple, D., Renwick, A., Thorne, F., 2015. Measuring and understanding the drivers of agricultural innovation: Evidence from Ireland. Food Policy 51, 1-8, http://dx.doi.org/10.1016/j.foodpol.2014.11.003.

LeSage, J.P., 2009. Introduction to Spatial Econometrics. CRC Press, Boca Raton.

LeSage, J.P., 2014. What Regional Scientists Need to Know about Spatial Econometrics. The Review of Regional Studies 44, 13-32, http://journal.srsa.org/ojs/index.php/RRS/article/view/44.1.2 (07.2015).

LeSage, J.P., Pace, R., 2014. The Biggest Myth in Spatial Econometrics. Econometrics 2, 217-249, http://dx.doi.org/10.3390/econometrics2040217.

Lindner, R.K., 1987. Adoption and diffusion of technology: an overview, in: Champ, B.R., Highly, E., Remenyi, J.V. (Eds.), Technological Change in Postharvest Handling and Transportation of Grains in the Humid Tropics. Australian Centre for International Agricultural Research, Canberra.

McNamara, K., Weiss, C., 2005. Farm Household Income and On- and Off-Farm Diversification. Journal of agricultural and applied economics 37, 37-48, http://dx.doi.org/10.1017/S1074070800007082.

Odgaard, M.V., Bøcher, P.K., Dalgaard, T., Svenning, J.-C., 2011. Climatic and non-climatic drivers of spatiotemporal maize-area dynamics across the northern limit for maize production: A case study from Denmark. Agriculture, Ecosystems & Environment 142, 291-302, http://dx.doi.org/10.1016/j.agee.2011.05.026.

Openshaw, S., 1984. The modifiable areal unit problem. Geo Books, Norwich.

Pace, R.K., Zhu, S., 2012. Separable spatial modeling of spillovers and disturbances. Journal of Geographical Systems 14, 75-90, http://dx.doi.org/10.1007/s10109-011-0155-7.

Padel, S., 2001. Conversion to Organic Farming: A Typical Example of the Diffusion of an Innovation? Sociologia Ruralis 41, 40-61, http://dx.doi.org/10.1111/1467-9523.00169.

Pannell, D.J., Marshall, G.R., Barr, N., Curtis, A., Vanclay, F., Wilkinson, R., 2006. Understanding and promoting adoption of conservation practices by rural landholders. Australian Journal of Experimental Agriculture 46, 1407-1424, http://dx.doi.org/10.1071/EA05037.

Pinkse, J., Slade, M.E., 2010. The future of spatial econometrics. Journal of Regional Science 50, 103-117, http://dx.doi.org/10.1111/j.1467-9787.2009.00645.x.

Piorr, A., Viaggi, D., 2015. The spatial dimension of Public Payments for Rural Development: Evidence on allocation practices, impact mechanisms, CMEF indicators, and scope for improvement. Ecological Indicators 59, 1-5, http://dx.doi.org/10.1016/j.ecolind.2015.05.060.

Quetier, F., Marty, P., Lepart, J., 2005. Farmers' management strategies and land use in an agropastoral landscape: roquefort cheese production rules as a driver of change. Agricultural Systems 84, 171-193, http://dx.doi.org/10.1016/j.agsy.2004.05.005.

Raggi, M., Sardonini, L., Viaggi, D., 2013. The effects of the Common Agricultural Policy on exit strategies and land re-allocation. Land Use Policy 31, 114-125, http://dx.doi.org/10.1016/j.landusepol.2011.12.009.

Rodríguez-Entrena, M., Arriaza, M., 2013. Adoption of conservation agriculture in olive groves: Evidences from southern Spain. Land Use Policy 34, 294-300, http://dx.doi.org/10.1016/j.landusepol.2013.04.002.

Roe, B., Irwin, E.G., Sharp, J.S., 2002. Pigs in space: modeling the spatial structure of hog production in traditional and nontraditional production regions. American journal of agricultural economics 84, 259-278, http://dx.doi.org/10.1111/1467-8276.00296.

Schmidtner, E., Lippert, C., Dabbert, S., 2015. Does Spatial Dependence Depend on Spatial Resolution? – An Empirical Analysis of Organic Farming in Southern Germany. German Journal of Agricultural Economics 64, 175-191, http://www.gjae-online.de/news/pdfstamps/outputs/GJAE-2e711cd0059c60b6b4df1834eb6bba61.pdf (01/2016).

Schmidtner, E., Lippert, C., Engler, B., Häring, A.M., Aurbacher, J., Dabbert, S., 2012. Spatial distribution of organic farming in Germany: does neighbourhood matter? European Review of Agricultural Economics 39, 661-683, http://dx.doi.org/10.1093/erae/jbr047.

Scholz, L., Meyer-Aurich, A., Kirschke, D., 2013. Bestimmungsfaktoren der Silomaisproduktion - Eine räumlich-ökonometrische Analyse, Schriften der GEWISOLA, Berlin, pp. 433-435, http://purl.umn.edu/156134 (07.2015).

Statistik Austria, 2013. Farm census 2010.

Statistik Austria, 2015. Feldfrucht- und Dauerwiesenproduktion, endgültiges Ergebnis 2014, https://www.statistik.at/web_de/statistiken/wirtschaft/land_und_forstwirtschaft/agrarstruktur_flaechen_ertraege/feldfruechte/080350.html (09.2015).

Storm, H., Mittenzwei, K., Heckelei, T., 2015. Direct Payments, Spatial Competition, and Farm Survival in Norway. American Journal of Agricultural Economics 97, 1192-1205, http://dx.doi.org/10.1093/ajae/aau085.

Styrian Chamber of Agriculture, 2015. Steirischer Marktbericht Nr. 38 zum 17. September 2015, https://stmk.lko.at/media.php?filename=download%3D%2F2015.09.18%2F1442574081136177.pdf&rn=Steirischer%20Marktbericht%20Nr.%2038%20zum%2017.%20September%202015.pdf (01.2016).

Styrian Pumpkin Seed Oil Community Association, 2015. Data of locations of washing and drying facilities and oil mills, Unpublished.

Thompson, S.R., Roland, H., Gohout, W., 2000. Agricultural Market Liberalization and Instability of Domestic Agricultural Markets: The Case of the CAP. American Journal of Agricultural Economics 82, 718-726, http://dx.doi.org/10.2307/1244631.

Tregear, A., Arfini, F., Belletti, G., Marescotti, A., 2007. Regional foods and rural development: The role of product qualification. Journal of Rural Studies 23, 12-22, http://dx.doi.org/10.1016/j.jrurstud.2006.09.010.

Useche, P., Barham, B.L., Foltz, J.D., 2009. Integrating Technology Traits and Producer Heterogeneity: A Mixed-Multinomial Model of Genetically Modified Corn Adoption. American Journal of Agricultural Economics 91, 444-461, http://dx.doi.org/10.1111/j.1467-8276.2008.01236.x.

Viaggi, D., Signorotti, C., Marconi, V., Raggi, M., 2015. Do agri-environmental schemes contribute to high nature value farmland? A case study in Emilia-Romagna (Italy). Ecological Indicators 59, 62-69, http://dx.doi.org/10.1016/j.ecolind.2015.01.017.

Weiss, C.R., 1999. Farm Growth and Survival: Econometric Evidence for Individual Farms in Upper Austria. American Journal of Agricultural Economics 81, 103-116, http://dx.doi.org/10.2307/1244454.

Wooldridge, J., 2012. Introductory econometrics: A modern approach, 5 ed. Cengage Learning.

3 Heterogeneous Preferences for Public Goods Provided by Agriculture in a Region of Intensive Agricultural Production: The Case of the Marchfeld

Abstract: The aim of this paper is to elicit the marginal willingness to pay (MWTP) for the improved provision of public goods (PGs) by agriculture in a region of intensive agricultural production, embodying many of the environmental problems related to agriculture within and outside the European Union (EU). Our analysis is based on a participatory approach, combining the involvement of local stakeholders and a discrete choice experiment (DCE) in the Marchfeld region in Austria. We estimate a random parameters logit model (RPL), including interactions with socio-demographic factors, in order to disentangle preference heterogeneity and find a positive MWTP of the local population for all three PGs analysed: (i) groundwater quality, (ii) landscape quality and (iii) soil functionality in connection with climate stability. Furthermore, MWTP varies considerably with respect to age, farmers/non-farmers and locals/incomers. Further research could combine the results of this demand-side valuation with those of a supply-side valuation, where the opportunity costs of different management options for farmers are estimated. Based on such a cost-benefit analysis and further participation of local stakeholders, new governance mechanisms for the smart and sustainable provision of PGs by agriculture could be developed for the Marchfeld region and for comparable European regions.

Keywords: discrete choice experiment; random parameters logit model; preference heterogeneity; willingness to pay; public goods; agriculture

3.1 Introduction

Agriculture faces increasing and opposing social and environmental challenges: due to population growth and changes in global dietary patterns, the global demand for (cheap) agricultural products remains high and is set to increase further (FAO, 2012). In many places, this demand leads to the intensification and spatial expansion of agricultural production, resulting in negative externalities for the environment (Brussaard et al., 2010) and the global climate (FAO, 2014).

With respect to climate change, agricultural production within the Land Use, Land Use Change and Forestry (LULUCF) sector is responsible for about 22% of the total anthropogenic greenhouse gas emissions (FAO, 2014). At a sectoral level, agriculture therefore causes emissions comparable to those produced by the global industry, the electricity and heat production sector (FAO, 2014). Regarding the environmental effects of an intensifying agriculture, numerous studies have shown negative environmental impacts on e.g. soils, water, biological or ecological diversity (FAO, 2003)[23]. Meanwhile, the environmental and social trade-offs of agricultural production are widely acknowledged and the related public and scientific debate is constantly evolving, leading to a growing recognition of sustainable production methods (OECD, 2017).

Within the European Union (EU) societal concerns regarding possible negative effects of agriculture on the environment are of particular relevance, as agricultural production receives respectable public support, making up around one third of agricultural income on EU-average (European Commission, 2017a). More and more, financial support to farms in the EU is therefore linked to the provision of social and environmental public goods (PGs) (Lowe et al., 2002; Randall, 2002; European Commission, 2017a). PGs are commonly characterised by non-rivalry and non-excludability (Samuelson, 1954), which means that their use by one individual does not reduce their availability to others and individuals cannot be excluded from its consumption. It is due to this two key-characteristics that even if there was a positive willingness to pay (WTP) by society for such PGs, there would still exist no market for them. PGs provided by agriculture are for example water quality, agricultural landscapes or

[23] It needs to be noted that also certain forms of extensive agricultural production may have a negative impact on the environment (e.g. extensive beef production could under certain conditions increase carbon emissions compared to more intensive forms of beef production) Pelletier et al. (2010).

functionality of soils. We would like to point out that while we focus on the concept of PGs in this article, substantial research on environmental valuation is also done using the framework of ecosystem services (ESS) (Costanza et al., 1997; Millenium Ecosystem Assessment, 2005; Fisher et al., 2009).

Despite an existing focus on the provision of PGs, the current agri-environmental policies of the EU fail to address environmental problems related to agriculture sufficiently, particularly in regions of intensive agricultural production (Viaggi et al., 2015), which are often situated at the fringe of larger urban agglomerations. Here, the trade-offs between agricultural production on the one hand, and the provision of PGs from the agro-ecosystems on the other, manifest themselves in increasing public debates about a more sustainable agricultural production. In its recent communication on ‘The Future of Food and Farming’ the European Commission has thus put forward a recommendation for the next reform of its Common Agricultural Policy (CAP), concluding that its future focus should be particularly laid on policies targeted towards achieving a smarter provision of PGs and addressing citizens’ concerns regarding sustainable agricultural production (European Commission, 2017b).

Against the background of the growing recognition of the trade-offs between agricultural production and the provision of PGs from agro-ecosystems, a growing number of studies has been dealing with the assessment of society’s demand for these goods. Due to the absence of a market for PGs, stated preference (SP) methods like contingent valuation (CV) or discrete choice experiments (DCEs) are often applied in order to estimate the demand for social and environmental PGs in general (Adamowicz et al., 1994; Birol et al., 2006) and those particularly affected by agriculture (Ragkos and Theodoridis, 2016; van Zanten et al., 2016). Alternatively, if PGs can be connected to a market good, it is also possible to apply revealed preference (RP) methods (Blow and Blundell, 2018). Valuation studies of PGs provided by agriculture comprise, for example, air quality and climate stability (Rodríguez-Entrena et al., 2012; Shoyama et al., 2013), (bio)diversity of agricultural landscapes (Sayadi et al., 2009; Häfner et al., 2017; Rodríguez-Entrena et al., 2017), soil functionality (Colombo et al., 2006; Hansen and Hellerstein, 2007) or (ground)water quality (Aizaki et al., 2006; Martin-Ortega and Berbel, 2010; Meyerhoff et al., 2014).

In addition, extensive research has already been carried out in order to analyse preference heterogeneity in DCEs, with respect to PGs provided by agriculture (Colombo et al., 2009; Aregay et al., 2016; Villanueva et al., 2016; Yang et al., 2016). Various statistical models have been developed, which attribute heterogeneity either to the deterministic or to the stochastic part of the model (Hess and Train, 2017). Beyond these different models, an informative approach is to investigate preference heterogeneity with respect to the socio-demographic characteristics of respondents such as gender, age or education level (see e.g. van Zanten et al. (2014b) for an overview of socio-demographic variables influencing preferences for agricultural landscapes).

Based on these considerations the aim of this paper is to elicit the marginal willingness to pay (MWTP) of local residents for the improved provision of PGs by agriculture in a typical region of intensive agricultural production, which embodies many of the environmental problems related to agriculture found in comparable regions within and outside the EU. Our analysis takes place in the Marchfeld region, a dynamically developing, semi-urban border region in Austria. Situated between the two capitals of Austria and Slovakia (Vienna and Bratislava) our case-study region (CSR) is marked by intensive agricultural production and at the same time rising concerns from the local population regarding a more sustainable agricultural land use. We apply a multi-stage stakeholder process in order to identify the main issues regarding the provision of PGs and target levels of their provision in the CSR. Based on a DCE, a conditional logit (CL) and random parameters logit (RPL) model are used to elicit the local population's MWTP for an increase in the provision of PGs by agriculture. In the analysis we particularly aim to identify factors driving differences in MWTP, such as socio-demographic characteristics or personal attributes.

Our paper contributes to the literature on valuation of public goods provided by agriculture in three ways: first, we focus on a region marked by intensive agricultural production which is situated at the fringe of large urban agglomerations. Such regions have received less attention in previous studies. Therefore, our analysis helps to gain better understanding of the complex local demand for PG-provision by agriculture in this specific regional context.

Secondly, we investigate and visualize the effects of socio-demographic factors on MWTP. Specifically, due to increasing in-migration from adjacent urban areas to the CSR, we also take into consideration the possible role of the origin of respondents (locals or incomers who have moved to the Marchfeld region) with respect to their preferences.

Thirdly, we provide additional estimates of MWTP for an increase in the provision of the three main PGs identified by local stakeholders in our CSR: groundwater quality, landscape quality and soil functionality for which we emphasise its connection with climate stability (Powlson et al., 2011).

The further structure of the paper is as follows: in the next section, we introduce our CSR, outline the process of PG-identification, describe our data basis and the choice experiment, as well as the econometric analysis. Subsequently, we proceed with the presentation and discussion of our results before providing concluding remarks.

3.2 Material and methods

3.2.1 Description of the case study region

Our CSR, the Marchfeld, is located in the north-east of Austria. It is a sedimentary basin between the Eastern Alps and the Carpathian Mountains and is characterised by a semi-arid climate with hot, dry summers and cold winters, very deep and fertile chernozem soils and a low annual precipitation of around 500 mm/year (BMLFUW, 2015).

The Marchfeld region consists of 23 municipalities covering 70,800 ha. The average population density is 97 persons/km², but it strongly varies in the single municipalities and ranges from 15 to 881 persons/km². For approximately the last 10-15 years, the region has experienced a strong population growth caused by in-migration (Statistik Austria, 2016). An overview of the location of the Marchfeld region is given in Figure 3.

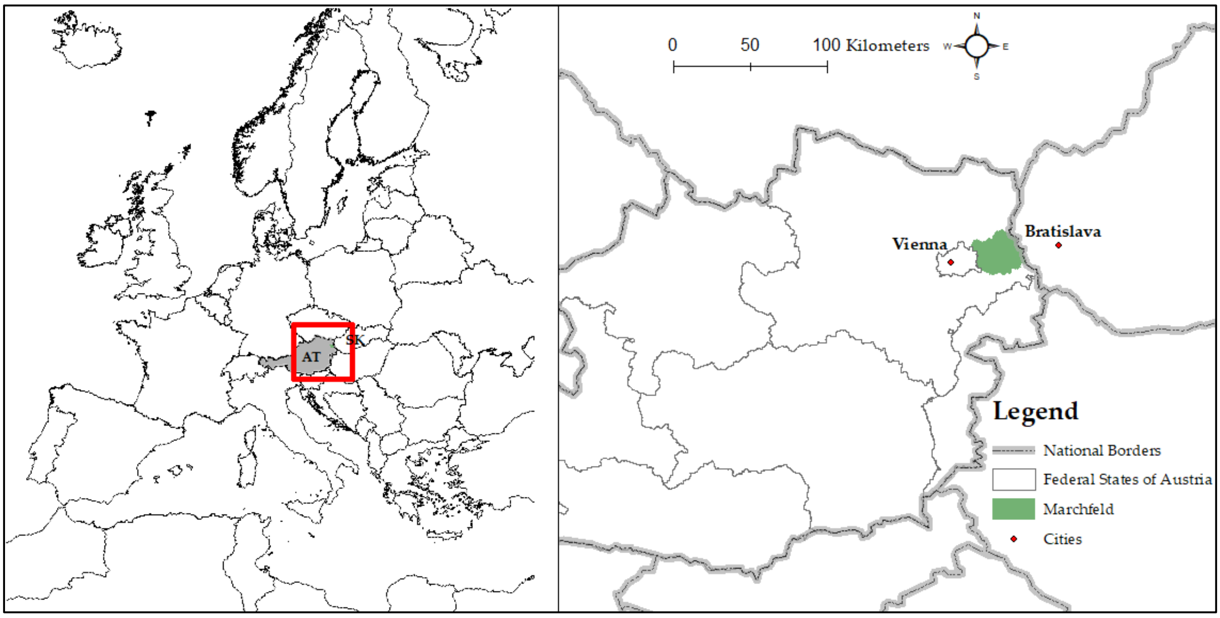

Figure 3. Location of Austria in Europe (left) and of the CSR Marchfeld within Austria (right)

Agricultural management is carried out on around 50,800 ha utilised agricultural area (UAA). Cash-crop farms make up around 95% and organic farms around 12% of all farms (roughly 900) in the CSR (BMLFUW, 2016). The good soil quality (BFW, 2018), combined with the possibility of irrigation, leads to an agricultural system characterised by intensive cash-cropping. 98% of UAA is made up of arable land (BMLFUW, 2016) and around 25% of agricultural area in the region is irrigated (Betriebsgesellschaft Marchfeldkanal, 2016).

The Marchfeld region is framed by two major agglomerations, Vienna and Bratislava. This leads to a multitude of sensitivities and claims affecting the region such as in-migration, recreation demands, space requirements for housing and infrastructural planning (e.g. roads, highways, flood protection) and regional food supply (Schaller et al., 2016).

3.2.2 Identification and validation of demand for public goods in the Marchfeld region

The main PGs, which are facing an imbalance between supply and demand and their target levels have been identified in a participatory process with local stakeholders, coming from the areas administration, agriculture, environment and rural development. In a first regional workshop, a group of stakeholders discussed what is understood by agricultural PGs and what problems exist with respect to their provision in the Marchfeld region. It became clear that there are many demands regarding agricultural production and the provision of PGs by agriculture. On the one hand, the Marchfeld region is highly suitable for the efficient and intensive production of food – with, in part, negative effects on PGs. On the other hand, mainly due to its spatial location, the Marchfeld region is a strong growth and inflow region, which in turn leads to increased demand, but also increased pressure on the provision of PGs by agriculture.

One major PG-issue identified by regional stakeholders and experts in the Marchfeld region is the functionality of the agricultural soils. Particularly due to intensive agricultural management, but also due to the climatic conditions in the Marchfeld region, soil fertility and soil health are assumed to be endangered, while simultaneously representing the most important basis for agricultural production. Soil conditions are identified by the stakeholders as intersecting with important environmental issues such as climate, groundwater, erosion, etc. Here, in particular the groundwater quality in the Marchfeld region is seen as a critical point. At the moment, groundwater quality in the Marchfeld region is very poor compared to other Austrian regions (BMLFUW, 2013). This is first and foremost due to the high level of nitrate pollution resulting from agricultural management, combined with the low precipitation rates leading to insufficient dilution. In many parts of the Marchfeld region, groundwater treatment is inevitable in order to reach the standard values for potable water. To improve soil functionality and consequently also to reach a positive impact on groundwater quality, changes of the agricultural management are suggested by the experts and stakeholders. These changes mainly include measures to increase soil-humus contents such as minimum tillage, intercropping and the mixing of straw, compost and harvest residues into the ground. In addition, changes in crop rotation are seen as potential ways to reduce chemical fertilization and enhance soil fertility. Further issues addressed in the stakeholder workshops were the agricultural landscape appearance and biodiversity (landscape quality). Due to intensive cash-cropping, the fields are on average relatively large and there is a lack of landscape elements like hedges and flower strips, which would make the landscape more diverse and additionally hamper wind erosion and promote biodiversity.

Despite existing agri-environmental policies in Austria, the above-mentioned problems remain in the Marchfeld region – suggesting the need for specifically tailored local agri-environmental policies. However, the decisive question is how the local population, which would be directly affected by such policies perceives the status-quo of PGs provided by agriculture and whether they would be willing to pay for an improvement in their provision. In order to assess the target levels of balanced provision of the three identified PGs soil functionality, groundwater quality and landscape quality, a second regional stakeholder workshop took place. Here, the necessary improvements in the levels of provision for the three main PGs were discussed and determined. In a third regional stakeholder workshop, the results of the DCE were presented to the stakeholders and discussed as regards their reliability and the driving factors behind those results.

3.2.3 Survey, choice sets and experimental design

We developed an online-questionnaire which consisted of (i) an introductory section, where the aim and scope of the study were presented; (ii) a section where participants were asked about their attitudes towards the three PGs of interest in the CSR; (iii) a choice experiment in order to receive information about their preferences and willingness to pay for an improvement in the three above-mentioned PGs; (iv) follow-up questions after the choice experiment in order to gain information about the motives and beliefs which drove their choices and their general view on PGs and agri-environmental policies and (v) a section on the socio-demographic characteristics of the participants.

In order to achieve an adequate sample size in the CSR, we cooperated with a market research institute. From a total of 559 people contacted, 204 people completed the survey. After removing 10 respondents due to protest responses (Meyerhoff and Liebe, 2008), 194 respondents represented the basis for the econometric analysis. The resulting sample was representative regarding age and gender and all participants were residents of the Marchfeld region (people had to specify their ZIP-code). Throughout the research process we followed the state of the art of environmental valuation with discrete choice experiments (Hoyos, 2010).

An overview of the attributes and their levels used in the choice experiment is given in Table 10. Groundwater quality can take on two levels: it is either potable only after a treatment, which is the case in the status quo, or potable without treatment. With respect to landscape quality we varied the percentage of hedges and flower strips on agricultural land from 2.5% (status quo) to 10%. The increasing percentage of hedges and flower strips was visualized with a Google-Earth image, which was edited with an image-editing program. For soil functionality in connection with climate stability, we presented respondents with different numbers of households for which the annual greenhouse-gas emissions (based on oil heating) are saved through implementation of conservation agricultural management practices (Knowler and Bradshaw, 2007). Those practices consist in our case of no tillage, intercropping and leaving residues on the field after harvesting, on certain proportions of agricultural land in the Marchfeld region. Aside from their positive impact on soil functionality, such practices can be a very cost-effective measure in reducing greenhouse-gas emissions through soil-carbon sequestration (Schneider et al., 2007). Specifically, conservation agricultural management practices on all the agricultural land in the Marchfeld region (~50,800 ha) or one percent (~508 ha) could save annual greenhouse-gas emissions caused by the oil heating of approximately 30,000 or 300 households respectively (Triebe, 2007; Austrian Energy Agency, 2017). Lastly, the payment vehicle was expressed as additional annual tax payments in €/household and year, ranging from €40 to €160. Only the status-quo option was associated with no additional payment.

Table 10. Attributes and levels used in the choice experiment

Attribute	Level	Description
Groundwater quality (water)	Groundwater potable only after treatment (status quo), Groundwater potable without treatment	Indicates, whether groundwater needs to be treated before it is potable
Landscape quality (landscape)	2.5 (status quo), 5, 7.5, 10	Percentage of hedges and flower strips on agricultural land
Soil functionality in connection with climate stability (climate)	0 (status quo); 10,000; 20,000; 30,000	Number of households for which the annual greenhouse gas emissions (oil heating) are saved
Additional tax payment (cost)	0 (status quo), 40, 80, 120, 160	Additional tax payment in €/household and year

All possible combinations of the attribute levels lead to a full factorial design with 128 alternatives. In order to reduce the number of combinations to a manageable size, we used a D optimal orthogonal design (Street et al., 2005) reducing the number of alternatives to 24, which we divided into four blocks. Each respondent was presented with six choice sets with two varying alternatives and the fixed status-quo alternative, leading to a total of 1,164 observed choices (= 194 x 6). An example of a choice set, which was translated to English, is given in Table 11.

Table 11. Example of a choice set used in the choice experiment (translated to English)

	Alternative A	Alternative B	Status Quo
Percentage of flower strips and hedges on agricultural area	 10%	 2.5%	 2.5%
Groundwater potable	only after treatment	without treatment	only after treatment
Saved annual GHG emissions	20,000 households	30,000 households	No GHG-emissions saved
Additional costs	80 €	120 €	0 €
I would choose	□ Alternative A	□ Alternative B	□ Status Quo

3.2.4 Econometric models and willingness to pay estimation

Building up-on the characteristics theory of demand, welfare theory and consumer theory (1966), the basis for the econometric analysis of our DCE are Random Utility Models (RUM) (1974). The principal idea is that utility ($\mathbf{U_{nj}}$) for an alternative j perceived by respondent n can be decomposed into an observed ($\mathbf{V_{nj}}$) and unobserved ($\boldsymbol{\varepsilon}_{\mathbf{nj}}$), stochastic part. Assuming that those parts are additive, one ends up with the following formula (Train, 2009)

$$\mathbf{U_{nj}} = \mathbf{V_{nj}} + \boldsymbol{\varepsilon}_{\mathbf{nj}}, \tag{13}$$

where the observed part of utility $\mathbf{V_{nj}}$ is assumed to be a weighted sum of attribute levels x of each alternative. Again, assuming that people choose between alternatives in order to maximize their utility, considering budget constraints, econometric models can be applied to estimate weights $\boldsymbol{\beta}$ for the attributes. The most basic RUM is the conditional logit model (CL), which assumes constant (homogeneous) parameters for each attribute over all respondents. The utility-specification of a CL model is given in the following formula (Train, 2009)

$$\mathbf{U_{nj}} = \boldsymbol{\beta}\mathbf{x_{nj}} + \boldsymbol{\varepsilon_{nj}}, \tag{14}$$

where $\mathbf{x_{nj}}$ is an attribute of alternative $\mathbf{j}$ for individual $\mathbf{n}$, $\boldsymbol{\beta}$ is a parameter of the attribute and $\boldsymbol{\varepsilon_{nj}}$ is an error term which is assumed to be identically and independently extreme value type 1 distributed (Gumbel-distribution). The researcher cannot observe utility, only the choices made by individuals, but one can estimate the parameters $\boldsymbol{\beta}$ which maximize the probability of the observed choices. A CL model has the following choice probabilities of individual n choosing alternative j over other alternatives, ranging from $\mathbf{1}$ to $\mathbf{K}$

$$\mathbf{P_{nj}} = \frac{\mathbf{e^{\beta x_{nj}}}}{\sum_{\mathbf{k=1}}^{\mathbf{K}} \mathbf{e^{\beta x_{nk}}}}, \tag{15}$$

and can be estimated by maximum likelihood (Train, 2009).

To overcome some restrictive assumptions of this model (no random taste variation, restrictive substitution patterns and no correlation of unobserved factors over time), more flexible models, such as the random parameters logit model (RPL), in a more general form also referred to as mixed logit model (MXL), have been developed (Train, 2009). An RPL model allows for some or all parameters to be individual-specific by assuming that they vary with density $\boldsymbol{\beta_n} \sim \mathbf{f}(\boldsymbol{\beta}|\boldsymbol{\theta})$, where $\boldsymbol{\theta}$ are the parameters, describing the distribution of $\boldsymbol{\beta}$ like for example means and variance-covariance matrix. This enables modelling unobserved preference heterogeneity across individuals. However, the distributional form of $\boldsymbol{\beta}$ has to be specified by the researcher. For example, when estimating an RPL model, where the parameters are assumed to be normally distributed, then the means and standard deviations of those $\boldsymbol{\beta}$ are estimated. Similar to (14), the utility-specification of an RPL model, where several choices for each individual are observed (panel RPL model), is given as

$$\mathbf{U_{njt}} = \boldsymbol{\beta}\mathbf{x_{njt}} + \boldsymbol{\varepsilon_{njt}}, \tag{16}$$

where $\mathbf{x_{njt}}$ is again an attribute of alternative $\mathbf{j}$ for individual $\mathbf{n}$ in choice situation $\mathbf{t}$, $\boldsymbol{\beta_n}$ is an individual-specific parameter and $\boldsymbol{\varepsilon_{njt}}$ is an error term which is again assumed to be identically and independently extreme value type 1 distributed (Gumbel-distribution). For a sequence of choices $\mathbf{j} = \mathbf{j_t}, \dots \mathbf{j_T}$ the choice probabilities conditional on $\boldsymbol{\beta}$ to observe a sequence of choices for person n is given as

$$\mathbf{P_{nj}} = \int \mathbf{L_{nj}}\,(\boldsymbol{\beta})\mathbf{f}(\boldsymbol{\beta})\mathbf{d}\boldsymbol{\beta}\,. \tag{17}$$

The log-likelihood function based on the sample of $\mathbf{N}$ individuals is, therefore, defined as:

$$\mathbf{LL(\theta)} = \sum_{n=1}^{N} \mathbf{ln}\left(\mathbf{P_{nj}}\right) = \sum_{n=1}^{N} \mathbf{ln}\left(\int \left(\prod_{t=1}^{T}\left(\frac{e^{\beta_n x_{nj_t t}}}{\sum_{k=1}^{K} e^{\beta_n x_{nkt}}}\right)\right)\mathbf{f(\beta|\theta)d\beta}\right). \tag{18}$$

Given that there is no closed form of $\mathbf{LL(\theta)}$, the probabilities are approximated through simulation for any given value of $\boldsymbol{\theta}$. The simulated log-likelihood function is, therefore, defined as

$$\mathbf{SLL(\theta)} = \sum_{n=1}^{N} \mathbf{l\,n}\left(\frac{1}{R}\sum_{r=1}^{R}\left(\prod_{t=1}^{T}\left(\frac{\exp(x'_{ni_{nt}t}\,\beta_r)}{\sum_{j=1}^{J}\exp\left(x'_{njt}\,\beta_r\right)}\right)\right)\right), \tag{19}$$

with the number of draws ranging from ranging from $\mathbf{1}$ to $\mathbf{R}$. The maximum simulated likelihood estimator is the value of $\boldsymbol{\theta}$ that maximises $\mathbf{SLL(\theta)}$ (Train, 2009).

The assumption that unobserved heterogeneity stems from preference heterogeneity across individuals is a very common one in environmental valuation with discrete choice models (Hoyos, 2010). The model can allow for correlation among utility coefficients, which can be, for example, caused by scale-heterogeneity (the magnitude of all random coefficients differs over people) (Hess and Train, 2017). Such a model is sometimes referred to as random parameters logit model with correlated effects and is able to capture all types of unobserved heterogeneity, including scale heterogeneity, but it cannot disentangle scale-heterogeneity from other unobserved sources of correlation (2017).

In logit models, one can only estimate the ratio of the coefficients and the variance of the error term and not the coefficients themselves. Due to this so-called scale-parameter, the estimated coefficients cannot be compared between different models, as they vary with the magnitude of unobserved heterogeneity. However, their signs still represent utility/disutility associated with the respective attribute (Hensher et al., 2015).

In order to provide a more meaningful interpretation of results, marginal rates of substitution between attributes can be calculated as the scale-parameter drops out, when the ratio of two coefficients is calculated. If the alternatives also include a cost-attribute, the MWTP in a CL model can be calculated as the ratio of the coefficient of a non-cost attribute $\boldsymbol{\beta_{nc}}$and the cost-attribute $\boldsymbol{\beta_c}$ multiplied by $\mathbf{-1}$.

$$\mathbf{MWTP_{nc}} = -\left(\frac{\beta_{nc}}{\beta_c}\right). \tag{20}$$

In an RPL model, MWTP is calculated in a similar manner, only instead of point estimates of the coefficients, their distribution is used. Also, confidence intervals can be calculated for the MWTP-estimates, using the Krinsky and Robb method (Train, 2009), which is based on simulating random draws from the respective distributions of the estimated random parameters. For MWTP-calculation, we use the median of the cost-attribute, as it is more robust to outliers due to the fat tail of a log-normal distribution (Bliemer and Rose, 2013).

Interaction effects of attributes $\mathbf{x}$ with respondent-specific information (e.g. socio-demographic variables $\mathbf{S}$) can be added to both of the models described above to further disentangle preference heterogeneity with respect to the observable part of utility (Kallas et al., 2007). Like in other regression models, the marginal effect of an attribute (which is defined as the first derivative of the specification with respect to the attribute) then depends not only on the coefficient of the respective non-cost attribute $\boldsymbol{\beta}_{\mathbf{nc}}$ and/or the respective cost attribute $\boldsymbol{\beta}_{\mathbf{c}}$, but also on the coefficient of their interaction between a socio-demographic variable and the respective attributes, which can be denoted as $\boldsymbol{\alpha}_{\mathbf{nc*S}}$ for a non-cost attribute and $\boldsymbol{\alpha}_{\mathbf{c*S}}$ for a cost attribute. These additional coefficients have to be further multiplied with a meaningful value of the respective socio-demographic variable, for example the median (denoted as $\tilde{\mathbf{S}}$), because the socio-demographic variable does not cancel out, when taking the first derivative. The same is true for the calculation of the MWTP, where the MWTP for a non-cost attribute would then be calculated as

$$\mathbf{MWTP_{nc}} = -\left(\frac{\boldsymbol{\beta}_{\mathbf{nc}} + \boldsymbol{\alpha}_{\mathbf{nc*S}} \cdot \tilde{\mathbf{S}}}{\boldsymbol{\beta}_{\mathbf{c}} + \boldsymbol{\alpha}_{\mathbf{c*S}} \cdot \tilde{\mathbf{S}}}\right). \qquad (21)$$

3.3 Results

3.3.1 Descriptive statistics

Descriptive statistics of the variables available for the econometric analysis are provided in Table 12. Apart from the attributes of the alternatives we created an alternative-specific constant (ASC) for the status-quo alternative, in order to gain information about the utility/disutility associated by respondents with the status-quo alternative. We also included an ASC for the second alternative as a means of controlling for other factors affecting choices in an unlabelled DCE (e.g. respondents having a tendency to choose the alternative placed in the middle). With respect to the attributes, we rescaled the climate-attribute, so that a unit-increase is associated with saving annual greenhouse-gas emissions of 10,000 households.

The socio-demographic variables can be used to disentangle possible preference heterogeneity in the econometric models based on observable characteristics. The average age of respondents is roughly in line with the average age of the population of the Marchfeld region. However, women are slightly overrepresented[24]. During the survey, participants were also asked for details of their level of education. Education ranges from 1 to 5, with 1 being compulsory school, 2 an apprenticeship or a middle school degree, 3 a high school degree, 4 a Bachelor's degree and 5 a Master's degree or higher. The resulting average education level of our sample is higher than the regional average. Other socio-demographic variables included were whether the respondents have children (45%), are farmers (9%) or are locals (74%). For farmers, we expected a lower utility for the PGs. Furthermore, we expected locals to have different preferences compared to people who moved to the Marchfeld region (incomers).

Table 12. Descriptive statistics of attributes and socio-demographic variables (N =194 respondents)

Variable	Description	Mean	Standard deviation	Minimum	Maximum
WATER	Groundwater quality attribute	0.33	0.47	0	1
LANDSCAPE	Rural landscape attribute	5	2.89	2.5	10
CLIMATE	Climate attribute	1	1.16	0	3
COST	Cost attribute	66.71	59.70	0	160
MALE	Respondent is male (1)	0.41	0.49	0	1
AGE	Age	40.53	14.28	16	76
EDUCATION	Education level	2.91	1.01	1	5
CHILDREN	Respondent has children (1)	0.45	0.50	0	1
FARMER	Farmer	0.09	0.28	0	1
LOCAL	Respondent is a local (1)	0.74	0.44	0	1

3.3.2 Econometric models

Estimation results of the CL and RPL models are provided in Table 13. The three models increase in complexity from left to right. The first two models (CL and RPL) are a conditional logit and random parameters logit model with an alternative-specific constant for the status-quo alternative, as well as the second alternative and no interaction terms. The third model (RPL-INT) is an RPL model, which also includes interaction terms with the socio-demographic variables in order to disentangle preference heterogeneity with respect to observed

[24] In order to assess whether this deviation has an effect on results, respondents were weighted by gender and age and those weights were used during the estimation of the econometric models. As this did not have any effect on results, the weights were not used for the final model specifications.

characteristics of respondents[25]. All models were estimated in R (R Development Core Team, 2018), using the gmnl-package (Sarrias and Daziano, 2017).

In general, the signs of the variables throughout the models are as expected and all of the attributes and the alternative-specific constant for the status-quo alternative are statistically different from zero at the 1%-level. In all three models, the ASC for the status-quo alternative is negative, meaning that respondents show disutility with respect to the status quo and therefore tend to prefer one of the other alternatives associated with an improvement in the provision of PGs by agriculture in the Marchfeld region compared to the status quo. The ASC for the second alternative is also negative and statistically significant at the 1% and 5%-level in the RPL and RPL-INT model. In combination with the negative sign of the ASC for the status-quo option, this indicates that, all else being equal, on average, respondents had a tendency to choose alternative A, i.e. the first column of the choice card in Table 11. Not considering such alternative-specific effects, even if they do not have an interpretational meaning, would lead to biased estimates of the other coefficients in the models (Adamowicz et al., 1998; Johnston et al., 2017). The coefficient of the cost attribute is also negative throughout all models, as expected. Therefore, an increase in cost has a negative effect on utility of respondents[26].

The decrease in Akaike Information Criterion (AIC) and increase of the Pseudo R^2, when moving from the CL model to the more complex models, illustrates a better fit of the more complex models, particularly when comparing the CL-model with the two RPL-models. In general, the pseudo R^2 lies in a range which is comparable to the results of similar environmental valuation studies (e.g. Rodríguez-Entrena et al., 2012). With respect to AIC, the RPL-INT-model has a worse fit than the RPL-model, as only some of the interaction terms with socio-demographic variables are statistically significant. Nevertheless, we keep all of the interaction terms in the model because we want to explore preference heterogeneity based on observable characteristics of respondents. Beginning with the CL-model, the positive

[25] We also estimated random parameters logit models with correlated effects, allowing for correlation between the random parameters. A comparison of the two competing model specifications (RPL and RPL-INT with and without correlated effects) based on a likelihood ratio test did not reveal any statistically significant differences between the models, which is why we present the models with uncorrelated effects as our final specifications.

[26] As can be seen in Table 13, the magnitude of the cost-coefficient changes, when moving from the MNL to the two RPL models. This is due to the assumed log-normal distribution. In order to get comparable values to the MNL model, one first has to calculate the mean or median of the log-normal variable. For example, the median is calculated by applying the exponential function to the estimated parameter.

coefficients of the three attributes mean that people derive utility from an increase in groundwater quality, landscape quality and climate-friendly soil management.

Table 13. Estimation results of the CL and RPL models

Independent Variable	Conditional logit (CL)		Random Parameters Logit (RPL)		Random Parameters Logit with interaction terms (RPL-INT)	
ASCSQ	-1.660	***	-3.211	***	-3.201	***
ASC2	-0.102		-0.294	***	-0.285	**
WATER	0.900	***	1.416	***	3.151	***
LANDSCAPE	0.095	***	0.150	***	0.057	
CLIMATE	0.276	***	0.539	***	0.639	
COST	-0.013	***	-4.018	***	-4.037	***
Mean shifters of random parameters						
WATER x MALE					0.136	
WATER x AGE					-0.031	***
WATER x EDUCATION					-0.035	
WATER x CHILDREN					0.311	
WATER x FARMER					-0.589	
WATER x LOCAL					-0.681	*
LANDSCAPE x MALE					-0.025	
LANDSCAPE x AGE					0.004	**
LANDSCAPE x EDUCATION					0.023	
LANDSCAPE x CHILDREN					-0.002	
LANDSCAPE x FARMER					-0.171	*
LANDSCAPE x LOCAL					-0.160	**
CLIMATE x MALE					0.163	
CLIMATE x AGE					-0.010	*
CLIMATE x EDUCATION					0.020	
CLIMATE x CHILDREN					0.135	
CLIMATE x FARMER					-0.079	
CLIMATE x LOCAL					0.175	
COST x MALE					0.144	
COST x AGE					-0.003	
COST x EDUCATION					0.019	
COST x CHILDREN					0.343	*
COST x FARMER					0.183	
COST x LOCAL					-0.173	
Standard deviations						
WATER			1.431	***	1.336	***
LANDSCAPE			0.220	***	0.188	***
CLIMATE			0.826	***	0.562	***
Additional model information						
Number of observations	1,164		1,164		1,164	
Number of individuals	194		194		194	
Number of Halton draws			5,000		5,000	
AIC	1,843		1,623		1,755	
Pseudo R^2	0.29		0.38		0.38	

****, ** and * and denote significance at the 1%, 5% and 10% levels respectively.*

In order to overcome the previously mentioned limitations of the CL model, the two RPL models were estimated, for which the three attributes groundwater quality, landscape quality and soil functionality in connection with climate stability were assumed to be normally distributed. For the cost-parameter, we assumed a log-normal distribution with changed sign, as this ensures that its coefficient takes on a negative sign (Bliemer and Rose, 2013). The results of both RPL-models were estimated with the simulated maximum likelihood method based on 5,000 Halton draws. In the basic RPL model without interactions, the magnitude of the coefficients of the three attributes increases, especially the coefficient of groundwater quality. This change in magnitude, in combination with high and statistically significant standard deviations of the random parameters, points towards the presence of unobserved preference heterogeneity, which cannot be captured in a CL model.

In order to disentangle observable preference heterogeneity, the RPL-INT model was estimated. From the available socio-demographic variables, AGE, CHILDREN, FARMER and LOCAL were statistically significant in combination with at least one attribute. Therefore, we only discuss the interaction effects of these variables more in detail. It is important to note that, in this model, the coefficients of the three attributes have a different meaning compared to the other two models, as the mean utility derived from a unit-increase in one attribute now also depends on the interaction effects and the values taken on by the socio-demographic variables.

The two interaction effects of AGE with WATER and CLIMATE are significant at the 1% and 10%-level respectively and have a negative sign. Thus, the positive utility associated with an improved groundwater quality and an increased climate-friendly management of agricultural land decreases with increasing age of respondents. The opposite is true for LANDSCAPE, where an increase in age is associated with an increase in utility of respondents.

Respondents who are farmers, show a lower preference for an increase in hedges and flower strips on agricultural land, which is indicated by the negative sign of the interaction effect of LANDSCAPE and FARMER. However, the effect is only statistically significant at the 10% level.

The variable CHILDREN is only statistically significant at the 10%-level when being interacted with the COST-attribute. The positive sign of the estimate means that people with children are more sensitive to additional costs, possibly indicating higher budget constraints for families with children.

Lastly, the variable LOCAL is statistically significant at the 10%- and 5%-level respectively, when being interacted with WATER and LANDSCAPE. In both cases the interaction effect has a negative sign, meaning that locals derive less utility from an increase in groundwater quality and landscape diversity, due to more hedges and flower strips on agricultural land.

3.3.3 Willingness to pay

Based on the RPL-INT model, we calculated summarised MWTP values by plugging in the median values of the socio-demographic variables into the calculation, described in (10). According to this results, respondents have a MWTP/household and year for groundwater which is potable without treatment of about €67.87, for an increase in hedges and flower strips on agricultural land by one percentage point of around €9.62 and for an increase of climate-friendly soil management on arable land by roughly 33 percentage points of €28.41 (representing saved greenhouse-gas emissions of 10,000 households caused by oil heating per year). However, due to the high preference heterogeneity, the WTP varies across respondents by a considerable degree.

In a second step we therefore illustrate the effect of the single socio-demographic variables on MWTP by letting one socio-demographic variable at a time take on its 5 and 95 percentile, while the others are held at their median value, offering a deeper insight into variations regarding MWTP. Figure 4 presents 25th and 75th percentiles of different simulated MWTP distributions based on the RPL-INT model. Gender, education level and the presence or absence of children does not seem to have a notable effect on MWTP. However, for the other three variables, variations in MWTP can be observed. For age, the median MWTP for potable groundwater without previous treatment in €/household and year varies between around €20 for older people (age of 65) up to around €100 for younger people (age of 19). A similar pattern can be observed for the climate-friendly management practices on agricultural land. Here, the MWTP varies between €11 and €36/household and year for saving emissions of 10,000 households, which is equivalent to climate-friendly management practices on one-third of the agricultural land in the Marchfeld region. With respect to an increase of hedges and flower strips on agricultural land we also observe differences in MWTP. However, the relationship is the reverse. While younger people are willing to pay around €2/household and year, older people are willing to pay around €16/household and year for a one-percentage-point increase in hedges and flower strips.

For farmers we observe a relatively clear tendency. They have a lower MWTP for all three PGs compared to non-farmers. This finding makes sense from a theoretical point of view: after all, farmers are the ones directly affected by the proposed changes in PGs. Specifically, the median of the MWTP-distribution of farmers and non-farmers varies between €17 and €68/household and year for groundwater, which is potable without treatment, virtually €0 and €9/household and year for an increase in hedges and flower strips by 1% and €17 and €27/household and year for climate-friendly management practices on one-third of the agricultural land in the Marchfeld region.

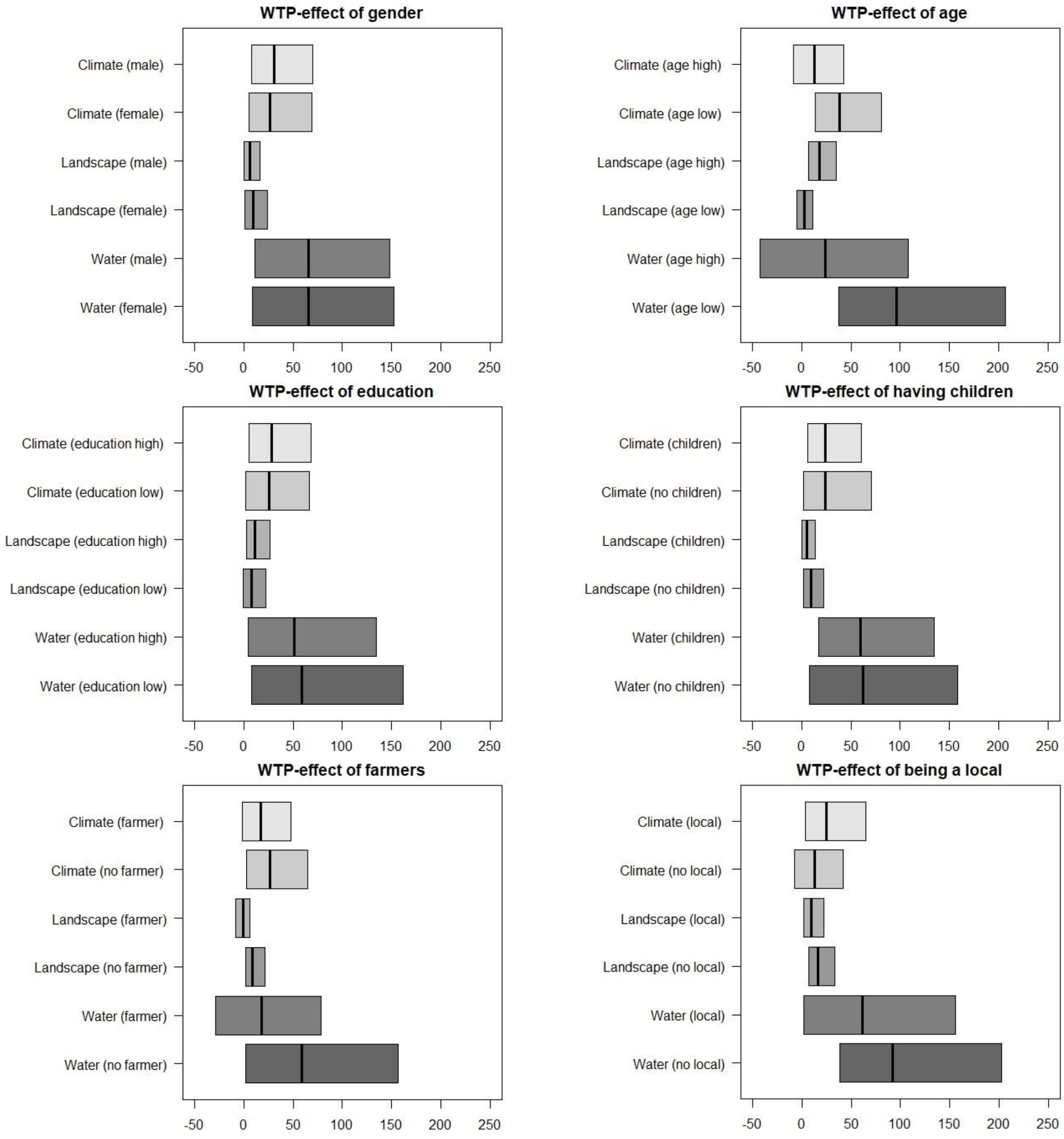

Figure 4. Effects of socio-demographic variables on MWTP

One final finding with respect to observed variations in MWTP relates to the origin of respondents. Locals seem to have a lower MWTP than incomers for potable groundwater without previous treatment (€66 compared to €87 / household and year) and a one-percentage-point increase in hedges and flower strips (€9 compared to €18/household and year), but a higher MWTP for climate-friendly management practices on agricultural land (€24 compared to €11/household and year). The lower MWTP for the first two attributes may reflect the fact that locals have known the region for a very long time and therefore perceive the current situation in the Marchfeld region as ‘normal’. Incomers, which have predominantly moved to the Marchfeld region from Vienna in the last decades, seem to be more sensitive to these PGs in their newly selected ‘homeland’. With respect to climate-stability, the situation is reversed. Here, it might be possible that locals are willing to pay more, because ‘their region’ may contribute to mitigating climate change, whereas incomers seem to put less emphasis on this aspect. However, it needs to be considered, that this last effect, despite its magnitude, is not statistically significant.

3.4 Discussion

3.4.1 Results

We now turn to the discussion of our results by first comparing our summarised MWTP-estimates with others found in the literature. For example, Latinopoulos (2014) finds a MWTP for an improvement in water quality of around €95.6, which is considerably higher than our results. However, as this study was carried out in a Mediterranean country, where water shortage is a considerable problem, hampering a direct comparison.

Moving on to landscape quality, a positive MWTP for more structured agricultural landscapes has been found throughout the literature (Borresch et al., 2009; van Zanten et al., 2014a; Rodríguez-Entrena et al., 2017), but a comparison is difficult due to a wide range of different specifications of the landscape-attributes, the region-specific context of the analyses and personal preferences of the respondents.

With respect to soil functionality in connection with climate stability, the estimated individual MWTP for saving a ton of CO^2 equivalent greenhouse gases lies in other studies between €4.35 x 10^6 and €1.74 x 10^4 (Rodríguez-Entrena et al., 2012). Taking our summarised MWTP as a basis, we receive a value of around €4.2 x 10^ 4, which lies in the upper range of estimated values. Thus, measures aimed at achieving a higher level of soil functionality may also contribute to climate-change mitigation.

As regards the stakeholder validation process of our results, the MWTP for the improvement of the three selected PGs stated by the inhabitants of the Marchfeld region was considered to be unexpectedly high. The stakeholders explained this result by a rising awareness of the local population with respect to the unsatisfying condition of the three PGs. The stakeholders assume that this is caused by the fact that inhabitants feel deteriorations of these three PGs on a daily basis in their landscape and water consumption, and in the extreme climatic conditions of the low precipitation area. As groundwater in the Marchfeld region has to be treated in order to be potable, there is an awareness of the fact that the groundwater quality is low. In addition, the lack of structural landscape diversity in the flat Marchfeld region is obvious in many parts of the area and the landscape is perceived by many inhabitants as being an “industrial” agricultural area. Nevertheless, according to the stakeholders, preferences for the three public goods, particularly the issue of landscape quality depend on individual preferences and could indeed be related to the provenance of the respondents, as incomers, who moved from the city to the Marchfeld region are often more sensitive for environmental issues. For the stakeholders, the results of the DCE are assumed to be transferable to other regions only to a limited extent, especially since the level of direct affectedness and the resulting awareness/concern about the conditions of the PGs play a major role in the magnitude of MWTP. The stakeholders expect a considerable shift of MWTP as soon as levels of affectedness change, e.g. if the panel of interviewees, are not located in the area itself.

3.4.2 Methodological considerations

As in any study, several methodological considerations need to be taken into account, when interpreting our results. Firstly, our data stems from an online survey. This survey-mode reduces cost and time for carrying out the survey as well as social desirability bias of respondents. However, at the same time it also reduces the control of how respondents perceive information during the experiment compared to face-to-face interviews and the sample composition is often skewed towards younger, well-educated respondents. A detailed overview of advantages and disadvantages of online-based SP methods can be found in Lindhjem (2011). Indeed, while our sample is representative with respect to gender and age, higher-educated people (education level between 3 and 5) are over-represented compared to the district where the CSR is located. Even though we did not find a statistically significant effect of education on MWTP, this aspect could potentially influence our results.

Secondly, it is also possible that our estimates suffer from a hypothetical bias (see for example Loomis et al. (Loomis et al., 2009) for an example in the context of water-quality valuation), which could lead to an overestimation of WTP. Even though this study used a contingent valuation approach, where such a bias is more likely to occur, we cannot rule this out. However, we provided respondents with a cheap talk script before the choice experiment, in which we informed them of this problem and asked them to make their choices as if in a real situation. Tonsor et al. (2011) show that cheap talk scripts can help to reduce hypothetical bias and arrive at more reliable estimates.

A third aspect concerns the basic assumption of rational utility maximization of respondents. More and more findings in behavioral economics show that this assumption does not always hold. For example, Foosgard et al. (2017) show in a public good game that even in simple choice situations a varying framing of the choice situation may substantially influence optimizing mistakes people make when choosing, leading to irrational choices. Brekke et al. (2017) show in another recent public good game that the framing of the contribution to the public good either in absolute monetary terms or relative to one's endowment and stated either as "contributing" to the public good or "keeping" some part of their own endowment influences how much people are willing to contribute. They find that a framing with "contributing" expressed in absolute monetary terms, causes people with low endowments (the "poor") to contribute significantly more than it would be the case in other, economically equivalent framings. This would suggest that our framing of the cost-attribute could lead to a higher MWTP for poorer people. Even though those findings are based on game-theoretic public good games, where people interact in groups and are therefore not directly comparable to our DCE, future research should control for such framing-effects.

3.5 Conclusions and policy implications

In the context of an upcoming reform of the Common Agricultural Policy (CAP) of the European Union (EU), which will most likely link payments to farmers more closely to a measurable provision of public goods, the aim of this paper was to elicit the marginal willingness to pay (MWTP) of local residents for the improved provision of public goods (PGs) by agriculture in a typical region of intensive agricultural production, which embodies many of the environmental problems related to agriculture within and outside the EU.

The analysis was carried out in the Marchfeld region, a dynamically developing, semi-urban border region in Austria which is marked by intensive agricultural production and at the same time rising concerns from the local population regarding a more sustainable agricultural land use. Based on a participatory approach, combining the involvement of local stakeholders and a discrete choice experiment (DCE), we find a positive and significant MWTP for all three PGs analysed, namely (i) groundwater quality, (ii) landscape quality and (iii) soil functionality in connection with climate stability.

Although our estimated MWTP values are in line with other findings in the literature (Borresch et al., 2009; Rodríguez-Entrena et al., 2012; Latinopoulos, 2014; van Zanten et al., 2014a; Rodríguez-Entrena et al., 2017), comparing MWTP in different regional settings based on slightly different attribute definitions remains challenging. Also, our estimated MWTP may still suffer from different sources of bias caused by the composition of the sample, the hypothetical nature of the DCE or non-compliance with the assumption of rational utility maximization of respondents. Nevertheless, having these general potential limitations of a SP approach in mind, our study is able to show that inhabitants of a typical region of intensive agricultural production in the EU have a positive MWTP for an improved provision of PGs by agriculture. Additionally, we show that MWTP varies considerably according to certain socio-demographic factors, specifically the age of respondents and whether they are farmers/non farmers or locals/incomers.

The integrative participation from local stakeholders we used throughout our research process helped us to gain a better understanding of the regional specifics regarding PG-provision. Moreover, it will facilitate further research on the development of more efficient governance mechanisms, based on participatory approaches (Targetti et al., (forthcoming)). Indeed, an enhanced stakeholder participation has also been acknowledged in the literature to contribute positively to tackling agri environmental problems (Beckmann et al., 2009). From our experiences we recommend an enhanced stakeholder participation, which should not only consist in the identification of environmental issues and the assessment of attributes and levels for DCEs, but also in the validation of and further work with results from such DCEs.

Our results can support policy makers in setting policy-priorities for the Marchfeld on the three PGs identified in this analysis. Of particular importance in this context are the observed differences in MWTP, which show that there are different groups within the population of the Marchfeld that have differing preferences with respect to PGs. In particular, an increasing share of incomers seems to imply higher preferences for the provision of PGs by agriculture. This finding should not only be of interest for policy makers responsible for the Marchfeld, but also for policy-makers in comparable regions which are also subject to increasing in-migration from adjacent cities. Notwithstanding, further research is needed to analyse how the differing claims of the population can be practically integrated into local land use concepts and to test, to what extent our findings can be transferred to other regions.

In general, a rising demand for the provision of PGs by agriculture may also generate social pressure on local farmers to adopt environmentally friendly management practices (Cumming et al., 2014). Indeed, farmers have both, the property rights for agricultural land and the skills to implement the improved provision of PGs, but at the same time lower preferences for the provision of PGs. Therefore, further research should aim at eliciting the willingness to accept (WTA) of farmers for the implementation of different management options in order to improve the provision of PGs (Beharry-Borg et al., 2013; Villanueva et al., 2016). This could ultimately result in a cost-benefit analysis, comparing estimated costs for farmers and the estimated gains for society. Such research would again have to carefully consider the regional context of the CSR due to a multitude of factors, influencing the adoption behaviour of farmers (Knowler and Bradshaw, 2007) and particularly also recent findings regarding green and social preferences of individuals (De Oliveira et al., 2015; Wichman, 2016) in order to design governance mechanisms which facilitate a socially optimal and sustainable provision of PGs in the Marchfeld and other European regions.

3.6 References

Adamowicz, W., Boxall, P., Williams, M., Louviere, J., 1998. Stated Preference Approaches for Measuring Passive Use Values: Choice Experiments and Contingent Valuation. American Journal of Agricultural Economics 80 (1), 64–75.

Adamowicz, W., Louviere, J., Williams, M., 1994. Combining Revealed and Stated Preference Methods for Valuing Environmental Amenities. Journal of Environmental Economics and Management 26 (3), 271–292.

Aizaki, H., Sato, K., Osari, H., 2006. Contingent valuation approach in measuring the multifunctionality of agriculture and rural areas in Japan. Paddy Water Environ 4 (4), 217–222.

Aregay, F., Yao, L., Zhao, M., 2016. Spatial Preference Heterogeneity for Integrated River Basin Management: The Case of the Shiyang River Basin, China. Sustainability 8 (10), 970.

Austrian Energy Agency, 2017. CO2-emissions of private homes. https://www.energyagency.at/fakten-service/heizkosten/co2-emissionen.html.

Beckmann, V., Eggers, J., Mettepenningen, E., 2009. Deciding how to decide on agri-environmental schemes: the political economy of subsidiarity, decentralisation and participation in the European Union. Journal of Environmental Planning and Management 52 (5), 689–716.

Beharry-Borg, N., Smart, J.C.R., Termansen, M., Hubacek, K., 2013. Evaluating farmers' likely participation in a payment programme for water quality protection in the UK uplands. Reg Environ Change 13 (3), 633–647.

Betriebsgesellschaft Marchfeldkanal, 2016. Daten, Fakten, Zahlen. http://www.marchfeldkanal.at/09main13h.htm (accessed 12 January 2018).

BFW, 2018. Digital soil map of Austria. http://gis.bmlfuw.gv.at/eBOD/frames/index.php?&gui_id=eBOD (accessed 12 January 2018).

Birol, E., Karousakis, K., Koundouri, P., 2006. Using a choice experiment to account for preference heterogeneity in wetland attributes: The case of Cheimaditida wetland in Greece. Ecological Economics 60 (1), 145–156.

Bliemer, M.C.J., Rose, J.M., 2013. Confidence intervals of willingness-to-pay for random coefficient logit models. Transportation Research Part B: Methodological 58, 199–214.

Blow, L., Blundell, R., 2018. A Nonparametric Revealed Preference Approach to Measuring the Value of Environmental Quality. Environmental and Resource Economics 69 (3), 503–527.

BMLFUW, 2013. Wasserinformationssystem Austria, Risiko mögliche Zielverfehlung 2021: Nitrat (2010-2012). http://maps.wisa.bmlfuw.gv.at/ist-bestandsanalyse-2013# (accessed 12 January 2018).

BMLFUW, 2015. Average annual precipitation in the Marchfeld. http://ehyd.gv.at/# (accessed 12 January 2018).

BMLFUW, 2016. Municipality Database: Version 5.0.

Borresch, R., Maas, S., Schmitz, K., Schmitz, P.M., 2009. Modeling the Value of a Multifunctional Landscape: A Discrete Choice Experiment. Paper presented at the International Association of Agricultural Economists Conference, Beijing, China. https://ageconsearch.umn.edu/bitstream/51641/2/IAAE2009_692.pdf (accessed 18 April 2018).

Brekke, K.A., Konow, J., Nyborg, K., 2017. Framing in a threshold public goods experiment with heterogeneous endowments. Journal of Economic Behavior & Organization 138, 99–110.

Brussaard, L., Caron, P., Campbell, B., Lipper, L., Mainka, S., Rabbinge, R., Babin, D., Pulleman, M., 2010. Reconciling biodiversity conservation and food security: Scientific challenges for a new agriculture. Current Opinion in Environmental Sustainability 2 (1-2), 34–42.

Colombo, S., Calatrava-Requena, J., Hanley, N., 2006. Analysing the social benefits of soil conservation measures using stated preference methods. Ecological Economics 58 (4), 850–861.

Colombo, S., Hanley, N., Louviere, J., 2009. Modeling preference heterogeneity in stated choice data: An analysis for public goods generated by agriculture. Agricultural Economics 40 (3), 307–322.

Costanza, R., d'Arge, R., Groot, R. de, Farber, S., Grasso, M., Hannon, B., Limburg, K., Naeem, S., O'Neill, R.V., Paruelo, J., Raskin, R.G., Sutton, P., van den Belt, M., 1997. The value of the world's ecosystem services and natural capital. Nature 387 (6630), 253–260.

Cumming, G.S., Buerkert, A., Hoffmann, E.M., Schlecht, E., Cramon-Taubadel, S. von, Tscharntke, T., 2014. Implications of agricultural transitions and urbanization for ecosystem services. Nature 515 (7525), 50–57.

De Oliveira, A.C.M., Croson, R.T.A., Eckel, C., 2015. One bad apple? Heterogeneity and information in public good provision. Exp Econ 18 (1), 116–135.

European Commission, 2017a. Share of direct payments and total subsidies in agricultural factor income (2011-15 average). European Union. https://ec.europa.eu/agriculture/sites/agriculture/files/cap-post-2013/graphs/graph5_en.pdf (accessed 12 January 2018).

European Commission, 2017b. The Future of Food and Farming. European Union, Brussels. https://ec.europa.eu/agriculture/sites/agriculture/files/future-of-cap/future_of_food_and_farming_communication_en.pdf (accessed 12 January 2018).

FAO, 2003. World agriculture: Towards 2015/2030: An FAO perspective. Earthscan Publications Ltd, London. http://www.fao.org/3/a-y4252e.pdf (accessed 18 April 2018).

FAO, 2012. World agriculture: Towards 2030/2050 - The 2012 Revision, Rome. http://www.fao.org/docrep/016/ap106e/ap106e.pdf (accessed 18 April 2018).

FAO, 2014. Agriculture, Forestry and Other Land Use Emissions by Sources and Removals by Sinks. Working Paper Series ESS/14-02. FAO Statistics Division. http://www.fao.org/docrep/019/i3671e/i3671e.pdf (accessed 18 April 2018).

Fisher, B., Turner, R.K., Morling, P., 2009. Defining and classifying ecosystem services for decision making. Ecological Economics 68 (3), 643–653.

Fosgaard, T.R., Hansen, L.G., Wengström, E., 2017. Framing and Misperception in Public Good Experiments. Scand. J. of Economics 119 (2), 435–456.

Häfner, K., Zasada, I., van Zanten, B.T., Ungaro, F., Koetse, M., Piorr, A., 2017. Assessing landscape preferences: A visual choice experiment in the agricultural region of Märkische Schweiz, Germany. Landscape Research 62 (2), 1–16.

Hansen, L., Hellerstein, D., 2007. The Value of the Reservoir Services Gained with Soil Conservation. Land Economics 83 (3), 285–301.

Hensher, D.A., Rose, J.M., Greene, W.H., 2015. Applied Choice Analysis. Cambridge University Press, Cambridge.

Hess, S., Train, K., 2017. Correlation and scale in mixed logit models. Journal of Choice Modelling 23, 1–8.

Hoyos, D., 2010. The state of the art of environmental valuation with discrete choice experiments. Ecological Economics 69 (8), 1595–1603.

Johnston, R.J., Boyle, K.J., Adamowicz, W., Bennett, J., Brouwer, R., Cameron, T.A., Hanemann, W.M., Hanley, N., Ryan, M., Scarpa, R., Tourangeau, R., Vossler, C.A., 2017. Contemporary Guidance for Stated Preference Studies. Journal of the Association of Environmental and Resource Economists 4 (2), 319–405.

Kallas, Z., Gómez-Limón, J.A., Arriaza, M., 2007. Are citizens willing to pay for agricultural multifunctionality? Agricultural Economics 36 (3), 405–419.

Knowler, D., Bradshaw, B., 2007. Farmers' adoption of conservation agriculture: A review and synthesis of recent research. Food Policy 32 (1), 25–48.

Lancaster, K.J., 1966. A New Approach to Consumer Theory. Journal of Political Economy 74 (2), 132–157.

Latinopoulos, D., 2014. Using a choice experiment to estimate the social benefits from improved water supply services. Journal of Integrative Environmental Sciences 11 (3-4), 187–204.

Lindhjem, H., 2011. Using Internet in Stated Preference Surveys: A Review and Comparison of Survey Modes. IRERE 5 (4), 309–351.

Loomis, J., Bell, P., Cooney, H., Asmus, C., 2009. A Comparison of Actual and Hypothetical Willingness to Pay of Parents and Non-Parents for Protecting Infant Health: The Case of

Nitrates in Drinking Water. Journal of agricultural and applied economics 41 (03), 697–712.

Lowe, P., Buller, H., Ward, N., 2002. Setting the next agenda?: British and French approaches to the second pillar of the Common Agricultural Policy. Journal of Rural Studies 18 (1), 1–17.

Martin-Ortega, J., Berbel, J., 2010. Using multi-criteria analysis to explore non-market monetary values of water quality changes in the context of the Water Framework Directive (eng). The Science of the total environment 408 (19), 3990–3997.

McFadden, D., 1974. Conditional logit analysis of qualitative choice behavior. In: Zarembka, P. (Ed.), Frontiers in Econometrics. Academic Press, New York.

Meyerhoff, J., Boeri, M., Hartje, V., 2014. The value of water quality improvements in the region Berlin–Brandenburg as a function of distance and state residency. Water Resources and Economics 5, 49–66.

Meyerhoff, J., Liebe, U., 2008. Do protest responses to a contingent valuation question and a choice experiment differ? Environmental and Resource Economics 39 (4), 433–446.

Millenium Ecosystem Assessment, 2005. Ecosystems and Human Well-Being: Synthesis, Washington, DC, 137 pp. http://millenniumassessment.org/documents/document.356.aspx.pdf (accessed 18 April 2018).

OECD, 2017. Green growth Indicators 2017. OECD Publishing, Paris.

Pelletier, N., Pirog, R., Rasmussen, R., 2010. Comparative life cycle environmental impacts of three beef production strategies in the Upper Midwestern United States. Agricultural Systems 103 (6), 380–389.

Powlson, D.S., Gregory, P.J., Whalley, W.R., Quinton, J.N., Hopkins, D.W., Whitmore, A.P., Hirsch, P.R., Goulding, K.W.T., 2011. Soil management in relation to sustainable agriculture and ecosystem services. Food Policy 36, S72-S87.

R Development Core Team, 2018. R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria.

Ragkos, A., Theodoridis, A., 2016. Valuation of environmental and social functions of the multifunctional Cypriot agriculture. Land Use Policy 54, 593–601.

Randall, A., 2002. Valuing the outputs of multifunctional agriculture. European Review of Agriculture Economics 29 (3), 289–307.

Rodríguez-Entrena, M., Barreiro-Hurlé, J., Gómez-Limón, J.A., Espinosa-Goded, M., Castro-Rodríguez, J., 2012. Evaluating the demand for carbon sequestration in olive grove soils as a strategy toward mitigating climate change (eng). Journal of environmental management 112, 368–376.

Rodríguez-Entrena, M., Colombo, S., Arriaza, M., 2017. The landscape of olive groves as a driver of the rural economy. Land Use Policy 65, 164–175.

Samuelson, P.A., 1954. The Pure Theory of Public Expenditure. The Review of Economics and Statistics 36 (4), 387.

Sarrias, M., Daziano, R., 2017. Multinomial Logit Models with Continuous and Discrete Individual Heterogeneity in R: The gmnl Package. J. Stat. Soft. 79 (2).

Sayadi, S., González-Roa, M.C., Calatrava-Requena, J., 2009. Public preferences for landscape features: The case of agricultural landscape in mountainous Mediterranean areas. Land Use Policy 26 (2), 334–344.

Schaller, L., Gerner, L., Kapfer, M., Kantelhardt, J., 2016. PROVIDE D3.2 - Report synthesizing the findings of the CSR level mapping of public good demand and supply, its underlying determinants, producers and beneficiaries: Annex 2: CSR Reports. CSR REPORT Austria. http://www.provide-project.eu/documents/2016/11/d3-2_annex-2_csr-report-it_de_at.pdf (accessed 30 April 2018).

Schneider, U.A., McCarl, B.A., Schmid, E., 2007. Agricultural sector analysis on greenhouse gas mitigation in US agriculture and forestry. Agricultural Systems 94 (2), 128–140.

Shoyama, K., Managi, S., Yamagata, Y., 2013. Public preferences for biodiversity conservation and climate-change mitigation: A choice experiment using ecosystem services indicators. Land Use Policy 34, 282–293.

Statistik Austria, 2016. Ein Blick auf die Gemeinde. http://www.statistik.at/blickgem/index.jsp (accessed 12 January 2018).

Street, D.J., Burgess, L., Louviere, J.J., 2005. Quick and easy choice sets: Constructing optimal and nearly optimal stated choice experiments. International Journal of Research in Marketing 22 (4), 459–470.

Targetti, S., Schaller, L., Kantelhardt, J., (forthcoming). A fuzzy cognitive mapping approach for the assessment of public goods governance in agricultural landscapes.

Tonsor, G.T., Shupp, R.S., 2011. Cheap Talk Scripts and Online Choice Experiments: "Looking Beyond the Mean". Am J Agr Econ Am J Agr Econ 93 (4), 1015–1031.

Train, K.E., 2009. Discrete Choice Methods with Simulation. Cambridge University Press, Cambridge.

Triebe, S., 2007. Möglichkeiten zur Verminderung von Treibhausgasemissionen aus der Landwirtschaft in den Bundesländern Brandenburg und Niedersachsen. Doctoral Thesis, Hohenheim.

van Zanten, B.T., Verburg, P.H., Espinosa, M., Gomez-y-Paloma, S., Galimberti, G., Kantelhardt, J., Kapfer, M., Lefebvre, M., Manrique, R., Piorr, A., Raggi, M., Schaller, L., Targetti, S., Zasada, I., Viaggi, D., 2014a. European agricultural landscapes, common agricultural policy and ecosystem services: a review. Agronomy for Sustainable Development 34 (2), 309–325.

van Zanten, B.T., Verburg, P.H., Koetse, M.J., van Beukering, P.J.H., 2014b. Preferences for European agrarian landscapes: A meta-analysis of case studies. Landscape and Urban Planning 132, 89–101.

van Zanten, B.T., Zasada, I., Koetse, M.J., Ungaro, F., Häfner, K., Verburg, P.H., 2016. A comparative approach to assess the contribution of landscape features to aesthetic and recreational values in agricultural landscapes. Ecosystem Services 17, 87–98.

Viaggi, D., Signorotti, C., Marconi, V., Raggi, M., 2015. Do agri-environmental schemes contribute to high nature value farmland?: A case study in Emilia-Romagna (Italy). Ecological Indicators 59, 62–69.

Villanueva, A.J., Rodríguez-Entrena, M., Arriaza, M., Gómez-Limón, J.A., 2016. Heterogeneity of farmers' preferences towards agri-environmental schemes across different agricultural subsystems. Journal of Environmental Planning and Management 60 (4), 684–707.

Wichman, C.J., 2016. Incentives, green preferences, and private provision of impure public goods. Journal of Environmental Economics and Management 79, 208–220.

Yang, X., Burton, M., Cai, Y., Zhang, A., 2016. Exploring Heterogeneous Preference for Farmland Non-market Values in Wuhan, Central China. Sustainability 8 (1), 12.

Appendix: Additional research and teaching activities

This appendix lists and describes additional activities of the author which were carried out during the doctorate. The additional activities are divided into the following areas:

- Presentations at international scientific conferences
- Research activities within the Horizon 2020 project PROVIDE
- Teaching within the H2020 project ENHANCE
- Further research activities
- Regular teaching at the University of Natural Resources and Life Sciences, Vienna (BOKU)

*Note: The additional activities of the author are categorised as follows: **contribution for a scientific conference based on a peer review, * contribution for a scientific conference based on a simple review, +report for research project, °publication for non-scientific audience, ~teaching.*

<u>Presentations at international scientific conferences</u>

Throughout the doctorate, the author of the thesis held several oral presentations and poster presentations at international conferences in the field of agricultural economics:

**Niedermayr, A., 2015. Measuring the influence of agglomeration effects on oil pumpkin cultivation in Austria: A spatial Tobit approach. Poster presentation at the ELLS Scientific Student Conference, Nov. 13-14 2015, Prague, Czech Republic.

**Niedermayr, A., Kapfer, M., Kantelhardt, J., 2016. Using econometric models to analyse the spatial distribution of oil pumpkin cultivation in Austria. Oral presentation at the 56th annual conference of the German Society of Economic and Social Sciences in Agriculture (GEWISOLA), Bonn, Germany. http://purl.umn.edu/244886 (accessed 18 June 2018).

**Niedermayr, A., Kantelhardt, J., 2017. Does aggregation lead to biased inferences? An empirical analysis of the adoption of oil-pumpkin cultivation in Austria at the farm- and municipality-level. Poster presentation at the 57th annual conference of the German Society of Economic and Social Sciences in Agriculture (GEWISOLA) and the 27th annual conference of the Austrian Society of Agricultural Economics (ÖGA), Freising-Weihenstephan, Germany.

**Niedermayr, A., Kantelhardt, J., 2017. 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. Poster presentation at the 15th congress of the European Association of Agricultural Economists (EAAE), Parma, Italy.

**Niedermayr, A., Schaller, L., Kieninger, P., Kantelhardt, J., 2018. Integrating soil and climate-related aspects into the valuation of willingness to pay for public goods provided by agriculture in an intensive agricultural production region: The case of the Marchfeld. Oral presentation at the 30th international conference of agricultural economists. International Association of Agricultural Economists (IAAE), Vancouver, Canada.

*Niedermayr, A., Schaller, L., Mariel, P., Kieninger, P., Kantelhardt, J., 2018. Valuation of willingness to pay for public goods provided by agriculture in a semi-urban intensive agricultural production region: The case of the Marchfeld. Oral presentation at the 164th Seminar of the European Association of Agricultural Economists (EAAE) - Preserving Ecosystem Services via Sustainable Agro-food Chains, Chania, Crete, Greece.

Research activities within the Horizon 2020 project PROVIDE

The second paper implemented in the thesis is based on research conducted in course of the EU Horizon 2020 project PROVIding smart DElivery of public goods by EU agriculture and forestry PROVIDE (www.provide-project.eu). The PROVIDE project involves 14 project partners from 13 EU countries and its objective is to develop a conceptual basis, evidence, tools and improved incentive and policy options to support the “smart” provision of public goods by the EU agriculture and forestry ecosystems. The subsequently listed documents are deliverables within the PROVIDE project, which were co-authored by the author of the dissertation.

+Villanueva, A.J., Rodríguez-Entrena, M., Gómez-Limón, J.A., Palomo-Hierro, S., Apostoaie, C.M., Bavorova, M., Berbel, J., Boevky, I., Borisov, P., Byg, A., Cañas, J.A., Chenais, M., Chapon, V., Couzier, J., D'Alberto, R., Desjeux, Y., Dupraz, P., Faccioli, M., Gerner, L., Gutiérrez-Martín, C., Häfner, K., Havova, R., Hujala, T., Juutinen, A., Kantelhardt, J., Kapfer, M., Keskpaik,, A., Kieninger, P.R., Komossa, F., Kurttila, M., Lassur, S., Le Goffe, P., Letki, N., Mäntymaa, E., Marconi, V., Maxim, A., Mihai, C., Mihnea, A., Mouléry, M., Napoleone, C., Niedermayr, A., Nikolov, D., Novo, P., Nshimiye, P., Paoli, J.C., Piorr, A., Radev, T., Raggi, M., Ratinger, T., Schaller, L., Stürzenbecher, F., Tafel-Viia, K., Tieskens, K., Tyrväinen, L., vn der Zanden, E., Vancurova, I., Verburg, P., Viaggi, D., Zagórska, K., Zasada, I., Zavalloni, M., 2017. PROVIding smart DElivery of public goods by EU agriculture and forestry: Deliverable D4.2: Report on valuation results. http://www.provide-project.eu/documents/2017/05/911.pdf (accessed 21 June 2018).

+Villanueva, A.J., Gómez-Limón, J.A., Raggi, M., D'Alberto, R., Viaggi, D., Anastasova, M., Apostoaie, C.M., Bareille, F., Bavorova, M., Berbel, J., Boevsky, I., Borisov, P., Byg, A., Cañas, J.A., Castillo, M., Couzier, J., Czajkowsky, M., Dupraz, P., Faccioli, M., Gerner, L., Guerra, F., Gutiérrez-Martín, C., Häfner, K., Havova, R., Juutinen, A., Kantelhardt, J., Kapfer, M., Keskpaik, A., Kieninger, P.R., Komossa, F., Kurttila, M., Lassur, S., Letki, N., Mäntymaa, E., Marconi, V., Maxim, A., Mihai, C., Napoleone, C., Niedermayr, A., Nikolov, D., Novo, P., Palomo-Hierro, S., Paoli, J.C., Piorr, A., Radev, T., Ratinger, T., Rodríguez-Entrena, M., Schaller, L., Stürzenbecher, F., Tafel-Viia, K., Tieskens, K., Tyrväinen, L., van der Zanden, E., Vancurova, I., Verburg, P., Zagórska, K., Zasada, I., Zavalloni, M., 2017. PROVIding smart Delivery of public goods by EU agriculture and forestry: Deliverable D4.3: Report on value determinants and transferability. http://www.provide-project.eu/documents/2017/11/d4-3-report-on-value-determinants-and-transferability.pdf (accessed 21 June 2018).

+Villanueva, A.J., Gómez-Limón, J.A., Rodríguez-Entrena, M., Byg, A., Roberts, M.J., Berbel, J., Castillo, M., D'Alberto, R., Faccioli, M., Gutiérrez-Martín, C., Häfner, K., Kantelhardt, J., Komossa, F., Marconi, V., Niedermayr, A., Novo, P., Piorr, A., Raggi, M., Sánchez-Cañizares, S., Schaller, L., Zasada, I., Zavalloni, M., Viaggi, D., 2018. PROVIding smart DElivery of public goody by EU agriculture and forestry: Deliverable 4.4: Report on public goods valuation guidelines. http://www.provide-project.eu/documents/2018/02/d4-4-report-on-public-goods-valuation-guidelines.pdf (accessed 21 June 2018).

Teaching within the H2020 project ENHANCE

The project Building an Excellency Network for Heightening Agricultural ecoNomic researCh and Education in Romania (ENHANCE) is a Coordination and Support Action (CSA) project, funded by the European Commission under the HORIZON 2020 Framework Programme (http://enhance-project.ro/). The aim of the ENHANCE project is to fully realise and to further develop the currently existing scientific potential of the agricultural economists of the University of Agronomic Sciences and Veterinary Medicine of Bucharest (USAMV), particularly with respect to quantitative methods like modelling, simulation, econometrics as well as mixed methods research like institutional economics. Apart from USAMV and BOKU the project partners include the Federal Department of Economics, Education and Research (Agroscope) and the Leibniz Institute of Agricultural Development in Transition Economies (IAMO). In course of the ENHANCE project the author of the dissertation is responsible for the following teaching activities at the USAMV:

~Development and teaching of a session on reference-management software in course of the USAMV Bucharest Agricultural Economics and Policy Summer School 2016 on Scientific Working. 01.09.-05.09.2016. Bucharest, Romania.

~Development and teaching of a 4-day training session on spatial econometrics at the USAMV Bucharest. Planned date: 24.09.2018-27.09.2018. Bucharest, Romania.

Further research activities

The author of the dissertation is currently also engaged in two further research activities. The first is related to a platform that investigates digitalisation in Austrian agriculture. Together with Leopold Kirner and Jochen Kantelhardt the current state of the art of digitalization in agriculture, developments and challenges with respect to farm management are investigated. The second research activity concerns a scientific project, which analyses the economic effects of the return of wolves on agriculture and particularly alpine-pasture management in Austria.

°Kirner, L., Niedermayr, A., Kantelhardt, J., (forthcoming). Handlungsfeld: Betriebswirtschaft und Management. In: Bundesministerium für Nachhaltigkeit und Tourismus (BMNT) (Ed.), Digitalisierung in der Landwirtschaft: Über den Stand der Entwicklung, die Herausforderungen und den Nutzen der neuen Technologien für die Landwirtschaft in Österreich. Ausarbeitung im Rahmen der Plattform "Digitalisierung in der Landwirtschaft" des BMNT, Wien.

°Hinterseer, A., Niedermayr, A., Kapfer, M., Kantelhardt, J. (forthcoming). Gutachterliche Stellungnahme zu den Auswirkungen von rückkehrenden Wölfen auf Landwirtschaft und traditionelle Weidehaltung, Freizeit- und Erholungswirtschaft, Jagd- und Forstwirtschaft sowie Biodiversität im Ostalpenraum: Teilbericht Agrarökonomie.

Regular teaching at the University of Natural Resources and Life Sciences, Vienna (BOKU)

The author of the dissertation also teaches regular courses at BOKU for Bachelor- and Master students and is additionally assisting in the supervision of bachelor- and master-theses.

~W2015-current: 733106 Bachelorseminar Agrar- und Ernährungswirtschaft (bachelor's thesis seminar – agricultural and food economy).

~W2015-current: 733315 Schwerpunkt-Seminar Landwirtschaftliche Betriebswirtschaftslehre (seminar farm business management).

~S2016-current: 733332 Betriebswirtschaftliche Projektstudie (business management project).

~S2016-current: 730305 Exkursion Agrar- und Ernährungswirtschaft. (field trip agricultural and food economy).