Farm-level adaptation to climate change

Julian Zeilinger, Andreas Niedermayr and Jochen Kantelhard[1]

***Abstract* - Adaptation of agriculture to climate change (CC) is a main goal within the European Union (EU). Therefore, it is crucial to assess the effectiveness of specific farm-level measures. This paper explores the CC adaptation of Austrian farms in arable regions, taking advantage of detailed information on soil conservation practice adoption. By employing an endogenous switching regression model (ESRM) for panel data we investigate the farm-level implementation of CC adaptation and its economic effect. Preliminary regression results suggest a significant effect of climatic conditions on the adoption of soil conservation.**

INTRODUCTION

Agriculture is going to be strongly influenced by increasing temperature and shifts in precipitation patterns, making it one of the most vulnerable economic sectors to CC in Europe. Consequently, the EU underlines the importance of mitigating its impacts. A key strategy to enhance the CC resilience of agriculture is farm-level implementation of specific CC adaptation measures. One example constitutes soil conservation (e.g. cover crops or reduced tillage), which aims to increase the moisture retention and subsequently yield (stability). This research investigates whether such farm-level CC adaptation decision is indeed economically effective for farms in Austrian arable regions – e.g. allowing them to better adapt to long-term and short-term (e.g. weather extremes) changes associated with CC.

METHODOLOGY

Implementing farm-level CC adaptation is voluntary, which means that adopters may systematically differ from non-adopters and cannot be seen as a random sample of the farm population. Unobservable characteristics of farms may affect both the CC adaptation decision and agricultural outcomes (Di Falco et al, 2011). A naive comparison of the two groups will thus most likely bias the effect of CC adaptation. To deal with this issue, Murtazashvili and Wooldridge (2016) developed an ESRM for panel data. The two-step model combines the Mundlak-Chamberlain approach to heterogeneity with the control function approach, which we follow hereafter. Firstly, we model the selection variable using a correlated random effect (CRE) Probit model. The selection variable indicates the adoption of CC adaptation, which in our case consists of cover crops and low-impact tillage (i.e. soil conservation). We assume that the decision to adapt is represented by a dichotomous choice model, where the implementation depends on the expected utility of CC adaptation:

$$Pr(Adapt_{it} = 1|z_{it}) \qquad (1)$$

where z_{it} denotes meteorological conditions (e.g. climate) as well as farm characteristics. These variables are later introduced in the outcome equation too, which is why two-step models have been criticized for potential misspecification due to multi-collinearity. In line with previous studies (Di Falco et al., 2011), we account for this by adding a set of selection instruments solely to the selection equation, affecting the decision to employ CC adaptation but not the outcome. Further, the Mundlak (1978) device ($\underline{z_i}$) is included, which represents the mean of each time-varying exogenous variable. This is done to control for unobservable characteristics and aims to substitute fixed-effects in nonlinear models. Finally, α and υ denote a time-trend and dummies for regions, respectively. In the second step, we estimate the relationship between the agricultural outcome and the control variables from the selection equation using an OLS estimator. We follow Murtazashvili and Wooldridge (2016) by including the generalized residuals from the Probit model to this outcome equation, in order to account for the endogeneity of the selection variable:

$$y_{it} = \beta_{00} + x_{it}\beta_{01} + \gamma_{10}Adapt_{it} + x_{it} * Adapt_{it}\gamma_{11} + \underline{z_i}\boldsymbol{\rho_0} + \underline{z_i} * Adapt_{it}\boldsymbol{\rho} \; \boldsymbol{\xi_0}\widehat{h_{it}} + \boldsymbol{\xi_1}\widehat{h_{it}} * Adapt_{it} + \boldsymbol{\delta_1}\alpha + \boldsymbol{\delta_2}\upsilon + \qquad (2)$$

where y_{it} is the net revenue per hectare of farm i in year t and x_{it} represents a vector of all meteorological and farm variables. Further, x_{it} is interacted with the selection variable $Adapt_{it}$, where γ_{11} denotes the difference between the coefficients of x_{it} (i.e. $\beta_{11} - \beta_{01}$) in the two regimes (Auci et al., 2021). In addition, the Mundlak device ($\underline{z_i}$) and the generalized residuals ($\widehat{h_{it}}$) from the Probit model as well as their interaction with the selection variable are included. Using the coefficients of Equation (2), it is possible to denote the treatment effect on the treated (TT) farms (Heckman and 2001). Therefore, the difference between the expected net revenues for those farms that actually implemented the CC adaptation measure and the counterfactual outcome if farms with CC adaptation had decided not to adopt is:

$$TT = E\left(y_{it}^{(1)}\middle|Adapt_{it} = 1\right) - E\left(y_{it}^{(0)}\middle|Adapt_{it} = 1\right) \qquad (3)$$

This represents the effect of CC adaptation (i.e. soil conservation) on the net revenues of adapted farms.

DATA

Our calculations are based on an unbalanced panel of individual farms in Austrian arable regions between 2003 and 2016. Data on soil conservation practices is

[1] Julian Zeilinger (julian.zeilinger@boku.ac.at), Andreas Niedermayr and Jochen Kantelhardt are from the University of Natural Resources and Life Sciences Vienna, Department of Economics and Social Sciences, Institute of Agricultural and Forestry Economics, Feistmantelstrasse 4, 1180 Vienna, Austria.

obtained from the Integrated Administration and Control System (IACS), which entails information on participation in the Austrian Agri-environmental Programme (ÖPUL). In particular, we account for the measures 'greening of arable land' (i.e. cover crops) and 'direct seeding and seeding on mulch'. Financial indicators, other characteristics and topographic information of individual farms are derived from the Austrian Farm Accountancy Data Network (FADN) data. Net revenue is calculated as the difference between revenues and costs in Euros per hectare. Further, we correct farm profits and subsidies using agricultural price indices from 'Statistics Austria'. Information on daily temperature and precipitation come from the 'Central Institute for Meteorology and Geodynamic' (ZAMG) at a resolution of 1x1km^2.

Preliminary Results

Based on our assertion that farms employing CC adaptation (i.e. soil conservation practices) and those who do not differ systematically, we first explore observable characteristic of both groups in Table 1. Farms with CC adaptation show both, higher net revenues and subsidies. Further, it is visible that adopting farms cultivate more area with a higher share of arable land. These variables might indicate that soil conservation practices are primarily implemented by larger arable farms. This is reinforced when considering topographical and plot-level information, which indicate flatter land with higher soil quality. Corresponding to existing studies, we also find higher temperatures and less precipitation for farms with CC adaptation (Teklewold and Mekonnen, 2017; Auci and Pronti, 2020).

Table 1. Descriptive statistics based on soil conservation.

	CC adaptation=1	CC adaptation=0
Farms	547	819
Net revenues (€/ha)	858.97 (559.89)	727.98 (655.67)
Subsidies (€/ha)	442.53 (113.86)	405.54 (149.46)
Farm area (ha)	50.21 (27.03)	33.84 (22.36)
Arable share (%)	78 (18)	45 (24)
Livestock (LU/ha)	0.75 (0.67)	0.89 (0.53)
Tractor (kw/100ha)	182.7 (71.1)	143.4 (61.0)
Education (1-4)*	3.41 (0.84)	2.96 (1.03)
Age (year born)	1962.1 (8.8)	1961.5 (10.0)
Altitude (m)	6.00 (3.87)	9.89 (6.03)
Slope (°)	357.2 (127.3)	484.1 (160.6)
Soil quality (0-100)*	52.37 (17.89)	32.21 (15.87)
$Temp_{20}^{a}$ (°C)	14.37 (0.88)	13.72 (1.11)
$Temp_{Dev}^{b}$ (°C)	0.51 (0.13)	0.46 (0.16)
$Prec_{20}^{a}$ (mm/month)	78.8 (14.6)	86.8 (14.3)
$Prec_{Dev}^{b}$ (mm/month)	0.7 (4.9)	-0.3 (6.1)

[a]20: 20-year moving average of weather (i.e. climate); [b]Dev: Deviation of annual weather from climate; *: Lowest value on the left; Standard deviation in parentheses.

Regarding the econometric analysis, we are currently developing a suitable set of variables explaining the implementation of CC adaptation. Based on previous literature (e.g. Hynes and Garvey, 2009; Auci and Pronti, 2020) we mainly focus on farmer, farm and topographic variables, resembling some of the characteristics in Table 1. Further, preliminary results of the CRE Probit model suggest that climatic conditions have a significant effect on the adoption of soil conservation, reinforcing our expectations and previous literature (Teklewold and Mekonnen, 2017).

Discussion and Outlook

Based on the comparison of key characteristics between adopters and non-adopters, we conclude that self-selection bias cannot be excluded and an ESRM has to be conducted. Therefore, our next step entails final specification of the CRE Probit model to uncover drivers and barriers of farm-level CC adaptation. Yet, the choice of selection instruments is not straightforward. While employing a large panel over several years allows us to capture adaptation induced by CC, it does not contain intrinsic characteristics of farmers (e.g. sustainable farming or CC awareness). A potential strategy includes employing proxies by accounting for ÖPUL participation (i.e. sustainable farming) and climate variability (i.e. experience of CC), respectively. First simple falsification tests indicate the validity of these instruments. In a final step, we aim to isolate the direct economic effects of soil conservation, in order to assess how CC adaptation affects the competitiveness of farms.

References

Auci, S., Barbieri, N., Coromaldi, M. & Michetti, M. (2021). Climate variability, innovation and firm performance: evidence from the European agricultural sector. *European Review of Agricultural Economics* 48(5):1074-1108.

Auci, S. & Pronti, A. (2020). Innovation in Irrigation Technologies for Sustainable Agriculture. *Sustainability Environmental Economics and Dynamics Studies* 1220.

Di Falco, S., Veronesi, M. & Yesuf, M. (2011). Does adaptation to climate change provide food security? A micro-perspective from Ethiopia. *American Journal of Agricultural Economics* 93(3):829-846.

Heckman, J., Tobias, J. L. & Vytlacil, E. (2001). Four parameters of interest in the evaluation of social programs. *Southern Economic Journal* 68(2):210-223.

Hynes, S. & Garvey, E. (2009). Modelling farmers' participation in an agri-environmental scheme using panel data: an application to the rural environment protection scheme in Ireland. *Journal of Agricultural Economics* 60(3):546-562.

Mundlak, Y. (1978). On the pooling of time series and cross section data. *Econometrica: journal of the Econometric Society* 69-85.

Murtazashvili, I. & Wooldridge, J. M. (2016). A control function approach to estimating switching regression models with endogenous explanatory variables and endogenous switching. *Journal of econometrics* 190(2):252-266.

Teklewold, H. & Mekonnen, A. (2017). The tilling of land in a changing climate: Empirical evidence from the Nile Basin of Ethiopia. *Land Use Policy* 67:449-459.