Evaluating the relation between crop diversity and productivity of Austrian crop farms

Simon Pröll, Klaus Salhofer and Andreas Eder[1]

***Abstract* – Crop diversity in agriculture is essential for sustainable and resilient agroecosystems. However, empirical evidence on the impact of crop diversity on farm performance for Europe is sparse. Using accounting data, we recover farm productivity from a production function utilizing semiparametric estimation techniques and relate it to various crop diversity indices derived from Integrated Administration and Control System (IACS) data. On average, we find that farms providing higher levels of crop diversity are associated with lower levels of productivity. Our findings highlight the need to incentivize farmers to provide public benefits associated with higher crop diversity.**

INTRODUCTION

Sustaining a high level of crop diversity in agriculture is essential for sustainable and resilient agroecosystems. Empirical evidence on the benefits of crop diversity can be found on several levels. On the global level, crop diversity is found to prevent population from diseases and foster food security. On the biological level, natural biodiversity can be increased through a high level of crop diversity providing the base for healthy soil, species complementarities and more efficient use of natural resources (Altieri, 1999). At the farm level, crop diversification reduces input- and output price risk, serves as a natural insurance against crop failure and allows for economies of scope.

Over the last decades, crop diversity decreased in most developed countries with farmers concentrating production on a few profitable crops entailing heavy use of chemicals and negative impacts on water, soil quality, wildlife and human health (Bellora et al., 2017). Diversification of crops allows pest reduction and suppression of diseases without applying chemical pesticides (He et al., 2019). Hence, in the last decades several measures to increase crop diversity have been introduced under the Common Agricultural Policy (CAP). Two examples are the greening measure 'crop diversification' and the Austrian agri-environmental scheme (ÖPUL) 'environmental friendly and biodiversity improving farming practices' (Umweltgerechte und biodiversitätsfördernde Bewirtschaftung). Therefore, for both farmers and policy makers it is crucial to know whether crop diversification translates into productivity gains.

Most existing studies focus on areas that differ considerably from Central European countries in terms of landscape and structure of agriculture (e.g. studies from Ethiopia or South Africa). We add to the literature by providing new evidence on the relation between crop diversity and productivity for Central Europe with Austria as a case study. In contrast to the widely used Fixed Effects (FE) estimator, our estimation procedure controls for unobserved and time-varying heterogeneity in production.

EMPIRICAL MODEL

Following Solow (1957), we consider productivity as the variation in output that cannot be explained by variation in inputs

$$\ln TFP_{it} = y_{it} - f(\boldsymbol{x}_{it}; \boldsymbol{\beta}). \tag{1}$$

Hereby, TFP_{it} denotes productivity of farm *i* in period t, output is captured by y_{it} and the function $f(\boldsymbol{x}_{it}; \boldsymbol{\beta})$ describes the transformation of inputs $\boldsymbol{x}_{it}$ into output y_{it} governed by a set of common technology parameters $\boldsymbol{\beta}$. We specify $f(\boldsymbol{x}_{it}; \boldsymbol{\beta})$ as translogarithmic and estimate $\boldsymbol{\beta}$ using the Ackerberg, Caves and Frazer (2015) (ACF) procedure. To avoid biased estimates of $\boldsymbol{\beta}$ that translate into biased estimates of TFP_{it}, the estimation procedure must control for any unobserved shocks that might be correlated to the level of input use. As a major advantage over the FE estimator, the ACF procedure does not only allow to control for time-invariant unobserved heterogeneity, but also for time-varying unobserved factors that might be known to the farmer but not to the econometrician.

Next, we relate productivity to crop diversity applying a semilogarithmic regression model in the second stage

$$\ln TFP_{it} = \gamma + \varphi div_{it} + \boldsymbol{\delta b}_{it} + \boldsymbol{d}_t + \nu_{it}, \tag{2}$$

where div_{it} captures farm *i*'s crop diversity in year t. Control variables are collected in the vector $\boldsymbol{b}_{it}$ and time fixed effects are captured by $\boldsymbol{d}_t$. The composite error $\nu_{it} = \alpha_i + \epsilon_{it}$ consists of farm fixed effects α_i, that are uncorrelated to the regressors, and the i.i.d. error ϵ_{it}. We estimate the model using the feasible generalized least squares estimator to appropriately control for the error structure in equation (2) when identifying the parameter of interest φ.

DATA

The data is drawn from the Austrian fraction of the Farm Accountancy Data Network (FADN). We use an unbalanced panel of 395 crop farms covering the period 2003 to 2019 whereas we only include agricultural holdings with a share of revenue from crops in total revenue larger or equal to 65.5%.

Farm output is measured as the sum of revenues from all agricultural activities net of all subsidies. Labor includes family labor and hired labor, and is measured in agricultural working units per year (AWU). Capital measures the average of a farm's capital stock at the beginning and at the end of the year. Material includes the sum of all expenses on

[1] Simon Pröll (simon.proell@boku.ac.at), Klaus Salhofer (klaus.salhofer@boku.ac.at) and Andreas Eder (andreas.eder@boku.ac.at) are from the University of Natural Resources and Life Sciences, Institute of Sustainable Economic Development, Vienna, Austria.

intermediate inputs. Land captures the utilized agricultural area in hectares and includes own and rented land. We normalize all input and output variables around the sample mean and deflate all variables in monetary terms by appropriate price indices.

The vector of controls $\boldsymbol{b}_{it}$ in equation (2) includes altitude in meters, a land quality index and farm location (dummy variables for main agricultural production areas). We calculate a Herfindahl-Hirschman index using seven categories of revenues (revenues from land use, livestock farming, forestry, renting out machinery and services to other farms, direct sales, subsidiary agricultural enterprises and agri-tourism) to control for farm specialization. Since much attention has been drawn to the effects of subsidies on productivity, we finally control for the level of subsidization. A drawback of measuring subsidies per hectare of UAA, as is common practice, is the potential lack of variation in this variable. Therefore, we include first- and second pillar CAP-payments per AWU.

Table 1 shows descriptive statistics of TFP and four different measures of crop diversity that are calculated using IACS data: the Simpson diversity index and the Pielou evenness index, both measured on a scale between 0 and 100; the Shannon-Weaver diversity index, theoretically taking on values between zero and infinity; and the number of crops.

Table 1. Descriptive statistics.

		Std.	Percentile	
	Mean	Dev	5%	95%
TFP	1.027	0.344	0.574	1.624
Simpson diversity index (0-100)	73.70	8.592	57.54	84.38
Shannon-Weaver diversity index	1.549	0.296	1.038	2.015
Pielou evenness index (0-100)	57.09	6.129	46.64	65.33
Number of crops	6.873	2.083	4	11

Results

Table 2 depicts parameter estimates of φ from equation (2) using different proxy variables for crop diversity div_{it}. We find negative coefficients for all crop diversity proxies. On average, a one-point increase in the Simpson diversity index translates into a 0.17% ceteris paribus (c.p.) decrease in TFP. Crop diversity coefficients are found to be significantly different from zero on a 10% level for the Simpson diversity index and Pielou's evenness index but insignificant for the Shannon diversity index or the number of crops planted.

To compare the c.p. impact of crop diversity on TFP, we compute the predicted difference in TFP between the 95th and the 5th percentile for our four diversity proxies. Using the Simpson diversity index and Pielou's evenness index, we hereby estimate values of -4.56% and -3.36% respectively. Using the Shannon-Weaver index and the number of crops as proxies, we estimate predicted differences in TFP between their 95th and the 5th percentile of -3.87% and -2.45% respectively.

Table 2. Relating TFP to crop diversity.

	Coeff.	R^2	Impact
Simpson diversity index (0-100)	-0.0017* (0.0009)	0.175	-4.56%
Shannon-Weaver diversity index	-0.0396 (0.0264)	0.173	-3.87%
Pielou evenness index (0-100)	-0.0018* (0.0011)	0.172	-3.36%
Number of crops	-0.0035 (0.0034)	0.172	-2.45%
Observations	4,151		

Heteroscedasticity robust standard errors in parentheses.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Conclusion

On average, we find that farms providing higher levels of crop diversity are associated with lower levels of TFP. Though, the estimated impacts are not statistically significant, the magnitudes may be relevant for farmers. The results are relatively robust to various measures of crop diversity. Our measure of TFP does not include any public benefits from higher crop diversity, such as enhanced biodiversity and ecosystem services. To the extent that these public benefits exceed TFP losses, compensations for crop diversity measures are justified. The results further show that the largest part of variation in productivity is explained by farms' natural conditions and the degree of subsidization.

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References

Ackerberg, D., Caves, K., and Frazer, G. (2015). Identification properties of recent production function estimators. *Econometrica*, *83*(6): 2411–2451.

Altieri, M.A. (1999). The ecological role of biodiversity in agroecosystems. *Agriculture, Ecosystems & Environment*, *74*(1): 19–31.

Bellora, C., Blanc, É., Bourgeon, J.-M., and Strobl, E. (2017). Estimating the Impact of Crop Diversity on Agricultural Productivity in South Africa. *NBER Working Paper*, *23496.*

He, H., Li-na, L., Shahzad, M., Bashir N.H., Yi, W., Yang J., and Cheng-yun, L. (2019). Crop Diversity and Pest Management in Sustainable Agriculture. *Journal of Integrative Agriculture,* 18,(9): 1945–52

Solow, R.M. (1957). Technical Change and the Aggregate Production Function. *The Review of Economics and Statistics*, *39*(3): 312–320.