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Shadow Values of Carbon Sequestration: A Case Study of the Czech Republic

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Abstract

This paper estimates the shadow values of total carbon sequestration in Czech cereal production. We use a production model with multiple outputs and inputs, using an input distance function (IDF) to estimate shadow price of land. The shadow prices of land and the amount of total carbon sequestration are then used to estimate the shadow values of carbon sequestration for a selected group of crops. The results present considerable differences in shadow values across both crops types and farm sizes.

Keywords

Carbon sequestration, shadow price, input distance function, FADN.

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Introduction

Carbon sequestration complements emission reduction efforts in aiding the European Union achieve its goal of becoming the first climate-neutral continent by 2050. In this context, the agricultural sector plays a unique role, as farming practices can both emit and absorb CO_2 (Aertsens et al., 2013). Policymakers have acknowledged this dual role, and carbon sequestration is now recognised and supported under the Common Agriculture Policy (CAP) as a means of achieving environmental objectives. The CAP 2023-2027 explicitly includes the objective: 'To contribute to climate change mitigation and adaptation, including by reducing greenhouse gas emissions and enhancing carbon sequestration, as well as to promote sustainable energy.'

However, carbon sequestration in agriculture faces several limitations that reduce its overall efficiency. The most significant challenge is the widespread practice of continuous cropping, which can severely degrade soil health. Continuous cropping often leads to the accumulation of autotoxic substances in the soil, causing harmful shifts in microbial community structure and diversity, and reducing soil nutrient levels. This degradation contributes to various soil health issues, including increased salinisation, acidification, and the spread of soil-borne diseases all of which inhibit crop productivity and, consequently, the soil's carbon sequestration potential (Ma et al., 2024; Chen et al., 2022). Nutrient depletion and microbial imbalances further restrict the effectiveness of carbon sequestration practices (Bao et al., 2022; Li et al., 2022).

In contrast, sustainable agricultural practices such as agroforestry, crop diversification, crop rotation, and reduced tillage significantly encourage soil carbon sequestration by enhancing plant biodiversity, minimising soil disturbances, and establishing stable deep root systems that contribute to carbon storage in both biomass and soil organic matter (McCauley and Barlow, 2023; Kaushal et al., 2023; Andrés et al., 2022; Sprunger et al., 2020).

Conservation practices, particularly conservation tillage and cover cropping, have been shown to improve soil structure, retain soil moisture, and reduce erosion, all of which contribute to enhanced carbon sequestration (Kaushal et al., 2023; Bossio et al., 2020). In addition, the implementation of good nutrient management and residue management practices further promotes carbon retention in the soil, which is essential for maintaining soil health and sustaining agricultural productivity (Kaushal et al., 2023).

Empirical evidence supports these findings. For example, Pawłowska et al. (2019) highlight the role of catch crop cultivation in enhancing CO_2 sequestration in the agricultural sector, demonstrating how the biomass of these crops contributes to increased carbon capture in soils. Using the case of cereal production in Poland, the study estimated that if the entire area currently used for cereal cultivation were converted to catch crops, between 4.1 and 6.6 tonnes CO_2 per hectare per year could be sequestered, depending on the plant species. Similarly, research by Kwiatkowski et al. (2020), conducted between 2016 and 2018 under the soil and climatic conditions of the central Lublin region in Poland, found that catch crops can sequester between 4 and 6 tonnes of CO_2 per hectare per year.

The importance of supporting these promising agricultural practices for carbon sequestration is acknowledged in both EU and national policies. The greening payments and their associated conditions under Pillar I, for instance, support practices that contribute to carbon sequestration. Requirements related to diversification of crops, the preservation of permanent grassland areas, and the designation of ecological focus areas align with research findings that highlight how biodiversity enhances carbon sequestration (McCauley and Barlow, 2023; Sprunger et al., 2020; European Parliament, 2015).

In Czechia, additional measures are being implemented under Pillar I through eco-schemes, which promote organic farming, reduced tillage, and agroforestry. These practices aim to improve soil health, increase biodiversity, and consequently enhance carbon sequestration (Ministry of Agriculture of the Czech Republic, 2022). Pillar II is, however, more directly linked to climate change mitigation, and its measures are therefore more specifically targeted at supporting carbon sequestration. For example, the Czech Republic has voluntarily adopted a range of agri-environment-climate measures under this pillar (Ministry of Agriculture of the Czech Republic, 2022).

To support data-driven policy design, this paper provides estimates of the shadow values of carbon sequestration based on the estimated shadow prices of land. Specifically, it contributes to the ongoing discussion on carbon sequestration by proposing a method for its economic valuation in agriculture.

The estimation of shadow values concerning the carbon mitigation has been explored in various contexts. For example, Zhou et al. (2014) present a literature review on analyses of 'bad' and 'good' outputs, while Guan et al. (2018) estimate the shadow prices of carbon emissions in Chiana's planting industry. The economic dimension of carbon sequestration is also addressed in Bamiere et al. (2014), who analyse carbon policy from the perspective of farmers' cost efficiency in France. In addition, Raj Kunwar et al. (2025) calculate different shadow prices for cover-crop fields and non-cover-crop fields, taking into account greenhouse gas emissions in order to promote the cover-crop adoption.

The novelty of this paper lies in the use of land shadow prices derived from a production model with multiple outputs and inputs, represented by an IDF. These are estimated using microeconomic data to calculate the shadow values of carbon sequestration.

The remainder of the paper is structured as follows. Chapter Material and methods presents data, theoretical model, and estimation procedure. Chapter Results and discussion discusses the results, and Chapter Conclusion provides concluding remarks.

Material and methods

Data

Our analysis relies on an unbalanced panel dataset of microeconomic data, comprising both physical and financial information on Czech agricultural producers. The data, sourced from the Farm Accountancy Data Network (FADN) and provided by the Institute of Agricultural Economics and Information, covers the period from 2008 to 2020. The sample includes farms classified according to the FADN typology as specialising in cereals, field crops, mixed cropping, and mixed crop-livestock operations.

The production technology is represented using an IDF, specified over vectors of outputs (y) and inputs (x). The output variables are defined as follows: cereal output (yC) corresponds to the value of cereal production; other crop output (yAOC) is calculated as the difference between total crop output and cereal output; and other agricultural output (yAOO) represents the difference between total farm output and total crop output.

The input variables include land (xL), measured in hectares of Utilised Agricultural Area (UAA); labour (xW), expressed in Annual Work Units (AWU); capital (xK), proxied by the sum of contract work and capital depreciation; and materials (xM), defined as total intermediate consumption, which refers to the sum of crop and livestock specific costs and general farming overheads, excluding contract work. The material input is used to normalise the remaining three input variables.

All monetary values for outputs and inputs are deflated using output and input specific price indices from Eurostat (base year 2010 = 100; Eurostat, 2021a–2021d). These deflators, together with farm characteristics such as a dummy variable for areas facing natural constraints (ANC), total subsidies per unit of output, and price indices of cereals, crops, and total output, are used as instrumental variables in the Generalised Method of Moments (GMM) estimation, alongside lagged IDF variables. Summary statistics for the input and output variables used in the analysis are presented in Table 1.

As the dataset does not contain complete information for all farms, observations from farms reporting negative or zero values for cereal production, land, labour, capital, or material inputs are excluded. To meet the requirements of the GMM estimator, producers with fewer than three observations are also removed. This approach helps to mitigate issues associated with unbalanced panel data. Additionally, in both models, the dependent variable and all covariates are log transformed and normalised by their respective means.

Theoretical model

The production process with multiple outputs and multiple inputs can, using production theory, be expressed in term of transformation function:

$$T(\mathbf{Y}_{\{it\}}, \mathbf{X}_{\{it\}}) = 1, \tag{1}$$

where $\mathbf{Y}$ represents a vector of m outputs and X is a vector of j inputs. The subscripts i and t denote farm ($i = 1, \ldots, N$) and time period ($t = 1, \ldots, T$), respectively.

The IDF is a special case of the transformation function that incorporates the behavioural assumption that the farmer can control inputs and seeks to minimise costs. In this case, the production technology is expressed by the input requirement set $L(y) = \{X{:}X\, can\, produce\, \boldsymbol{Y}\}$, with $\boldsymbol{X} \in \Re_{+}^{J}$ to produce $\boldsymbol{Y} \in \Re_{+}^{M}$. The input requirement set is assumed to be closed, convex, and bounded by the input isoquant: $Isoq\ L(\boldsymbol{Y}) = \{\boldsymbol{X}{:}X \in L(\boldsymbol{Y}), \lambda(\boldsymbol{X}) \notin L(\boldsymbol{Y}), \lambda < 1\}$, where both inputs and outputs are assumed to be strongly, or freely, disposable (see Kumbhakar and Lovell, 2000).

According to Shephard (1970), the IDF is a radial measure of the distance from the output vector $\mathbf{Y}$ to the input isoquant, $Isoq\ L(\boldsymbol{Y})$:

$$D_{I(Y,X)} = sup\ \{\mu > 0 : (\ \boldsymbol{Y}/\mu) \ \epsilon\ L(\boldsymbol{Y})\}, \tag{2}$$

where μ represents the maximum possible proportional reduction in input vector $\mathbf{X}$ for a given output level $\mathbf{Y}$ (Zhou et al., 2014).

Under the assumption of linear homogeneity of degree one in inputs, the IDF satisfies:

$$D_I\,(Y_{\{it\}}, X_{\{it\}}) = 1. \tag{3}$$

In our empirical analysis, we assume that the transformation process can be well approximated by the translog multiple inputs and outputs IDF:

$$\begin{aligned}
\ln D_{Iit} = {} & \alpha_0 + \sum_{m=1}^{M} \alpha_m \ln y_{mit} + \\
& + \frac{1}{2}\sum_{m=1}^{M}\sum_{n=1}^{M} \alpha_{mn} \ln y_{mit} \ln y_{nit} + \sum_{k=1}^{K} \beta_k \ln x_{kit} + \\
& + \frac{1}{2}\sum_{k=1}^{K}\sum_{l=1}^{K} \beta_{kl} \ln x_{kit} \ln x_{lit} + \sum_{k=1}^{K}\sum_{m=1}^{M} \gamma_{km} \ln x_{kit} \ln y_{mit} + \\
& + \delta_t t + \frac{1}{2}\delta_{tt} t^2 + \textstyle\sum_{m=1}^{M} \alpha_{mt} t \ln y_{mit} + \\
& + \textstyle\sum_{k}^{K} \beta_{kt} t \ln x_{kit},
\end{aligned} \tag{4}$$

where α, β, γ and δ are vectors of the technology parameters to be estimated.

Variable	Obs	Mean	Std.Dev	Min	Max
yC	7,252	6617338	8925003	6303	93000000
yAOC	7,252	7310124	10900000	0	117000000
yAOO	7,252	10100000	18400000	0	172000000
xM	7,252	19600000	27600000	106503	232000000
xL	7,252	757.3	882.5	8.0	5980.1
xW	7,252	19.2	26.6	0.4	215.4
xK	7,252	3795198	5234101	7469	50100000

Source: FADN, own calculations

Table 1: Descriptive statistics of outputs and inputs.

We impose homogeneity[1] by normalising all the inputs by x_1 (material inputs, *xM*):

$$
\begin{aligned}
-\ln x_{1it} = {} & \alpha_0 + \sum_{m=1}^{M} \alpha_m \ln y_{mit} + \\
& + \frac{1}{2} \sum_{m=1}^{M} \sum_{n=1}^{M} \alpha_{mn} \ln y_{mit} \ln y_{nit} + \sum_{k=2}^{K} \beta_k \ln x^*_{kit} + \\
& + \frac{1}{2} \sum_{k=2}^{K} \sum_{l=2}^{K} \beta_{kl} \ln x^*_{kit} \ln x^*_{lit} + \sum_{k=2}^{K} \sum_{m=1}^{M} \gamma_{km} \ln x^*_{kit} \ln y_{mit} + \\
& + \delta_t t + \frac{1}{2} \delta_{tt} t^2 + \sum_{m=1}^{M} \alpha_{mt} t \ln y_{mit} + \\
& + \sum_{k}^{K} \beta_{kt} t \ln x^*_{kit} + \eta_i + \varepsilon_{it},
\end{aligned} \tag{5}
$$

where $x^*_{kit} = \frac{x_{kit}}{x_{1it}}$. η_i captures the firm heterogeneity and ε_{it} is a stochastic noise, which is supposed to be i.i.d. $x^*_{kit} = \frac{x_{kit}}{x_{1it}}$. η_i .[2]

Estimation procedure

We estimate the IDF using the two-step system GMM estimator, which addresses potential endogeneity in equation (3). This approach relies on a system of two equations: one specified in first differences and the other in levels. It uses two types of internal instruments: lagged levels of the IDF variables for the differenced equation and lagged differences of the IDF variables for the levels equation. In addition, a set of external instruments (additional variables in levels) are employed to improve identification. The validity of the instruments is tested using the Hansen J-test (Hansen, 1982), which verifies the overall orthogonality of the instruments. We also conduct the Arellano-Bond test for autocorrelation (Arellano and Bond, 1991), which evaluates the appropriateness of using lagged variables as instruments.

Results and discussion

Table 2 presents the parameter estimates of the IDF. The signs of the first order coefficients are consistent with economic theory. Specifically, the estimates indicate that the IDF is non-increasing in outputs and non-decreasing in inputs. Furthermore, the model satisfies the requirement of concavity in inputs. The estimates also exhibit strong statistical properties, with most first order parameters statistically significant at the 5 percent level. Moreover, the Wald test (at $\alpha = 0.05$) rejects the null hypothesis that all second order parameters are jointly equal to zero. This result supports the use of the translog functional form over the less flexible but widely used Cobb-Douglas production function. Specifically, the test suggests that adopting a Cobb-Douglas specification could yield biased estimates, as it does not account for variation in the first order parameters. For example, the second derivatives with respect to specific inputs or outputs are restricted to zero. The Hansen's J-test and the AR(2) test further support the validity of the GMM specification.

Since the translog IDF is estimated using logarithmic transformations of all variables, normalised by their sample means, the first order parameters can be interpreted as output and input elasticities or as shadow output and input shares, evaluated at the sample mean. Table 2 reports these shares, which reflect the relative contribution of each output and input to the production process. The results indicate a high level of specialisation in cereal production, which accounts for 51 percent of output (when evaluated under constant returns to scale). The share of other crop output is 34 percent, while other agricultural output accounts for approximately 15 percent. The estimates of economies of scale implies that the production process exhibits increasing returns to scale, with a scale elasticity of 1.143. This suggests that farms in the sample demonstrate minor economies of scale.

Moreover, agricultural production in the sample is material intensive, with material inputs dominating the cost structure. The material shadow share is 0.498, while the shadow shares of other material inputs range between 0.15 and 0.2. Specifically, land accounts for 0.145, labour for 0.196, and capital for 0.161.

The time variable parameter indicates technological regress; however, this regress slows over time. Hicks-neutral technological change was not rejected at the 5 percent significance level, suggesting that the technological change maintains the same input structure.

Table 3 presents the estimated shadow prices of land, calculated as the partial derivatives of the IDF with respect to land, alongside the actual rent paid by farms. The results indicate that shadow prices of land per hectare are higher than rent paid per hectare, suggesting considerable allocative inefficiencies in agriculture production. Specifically, land appears to be underutilised in farm production. This holds for the full sample

[1] Homogeneity of degree 1 in inputs implies: $\sum_{k=1}^{K} \beta_k = 1$, $\sum_{k=1}^{K} \beta_{kl} = \sum_{k=1}^{K} \beta_{kt} = \sum_{k=1}^{K} \gamma_{km} = 0$

[2] Symmetry restrictions are: $\alpha_{mn} = \alpha_{nm}$ and $\beta_{kl} = \beta_{lk}$

Variable	Coefficient	Std.Err.	P-value	Variable	Coefficient	Std.Err.	P-value
ln_yC	-0.4494	0.0203	0.0000	t	0.0339	0.0027	0.0000
ln_yAOC	-0.2978	0.0176	0.0000	t_2	-0.0073	0.0011	0.0000
ln_yAOO	-0.1280	0.0068	0.0000	ln_yCt	-0.0004	0.0012	0.7080
ln_xL	0.1445	0.0354	0.0000	ln_yAOCt	0.0035	0.0016	0.0330
ln_xW	0.1962	0.0265	0.0000	ln_yAOOt	0.0003	0.0003	0.2360
ln_xK	0.1612	0.0208	0.0000	ln_xLt	0.0135	0.0072	0.0590
ln_yC_2	-0.0414	0.0021	0.0000	ln_xWt	0.0026	0.0052	0.6200
ln_yAOC_2	-0.0264	0.0017	0.0000	ln_xKt	0.0040	0.0045	0.3800
ln_yAOO_2	-0.0150	0.0010	0.0000	ln_yCxL	0.0274	0.0096	0.0040
ln_yCyAOC	0.0136	0.0038	0.0000	ln_yAOCxL	0.0036	0.0195	0.8550
ln_yCyAOO	0.0018	0.0004	0.0000	ln_yAOOxL	-0.0173	0.0035	0.0000
ln_yAOCyAOO	-0.0011	0.0007	0.0870	ln_yCxW	-0.0121	0.0066	0.0690
ln_xL_2	-0.6763	0.1324	0.0000	ln_yAOCxW	-0.0400	0.0163	0.0150
ln_xW_2	-0.0730	0.0694	0.2930	ln_yAOOxW	-0.0085	0.0027	0.0010
ln_xK_2	0.0880	0.0299	0.0030	ln_yCxK	-0.0038	0.0047	0.4200
ln_xLxW	-0.0228	0.0551	0.6790	ln_yAOCxK	0.0033	0.0047	0.4810
ln_xLxK	0.0009	0.0442	0.9830	ln_yAOOxK	-0.0013	0.0019	0.4780
ln_xWxK	-0.0918	0.0299	0.0020	constant	0.7698	0.0319	0.0000
Arellano-Bond test for AR(2) in first differences: z = -0.69 Pr > z = 0.493							
Hansen test of overid. restrictions: chi2(872) = 797.92 Prob > chi2 = 0.965							

Source: own calculations

Table 2: IDF parameter estimate.

Shadow prices of land according to the size (CZK/ha)					
	Full sample	0 - 99 ha	100 - 499 ha	500 - 999 ha	1000 and more ha
Mean	4377.8	2112.7	1310.2	5487.0	8725.0
Median	2570.9	955.3	431.2	3698.0	7988.0
Rent paid (CZK/ha)					
	Full sample	0 - 99 ha	100 - 499 ha	500 - 999 ha	1000 and more ha
Mean	2269.0	2029.0	2148.0	2563.4	2431.7
Median	2002.0	1610.0	1945.0	2427.4	2280.0

Source: own calculations

Table 3: Shadow prices of land and rent paid.

as well as for all size categories evaluated using mean values. However, when using the median, the results show that shadow prices of land are lower than the rent paid for farms up to 499 hectares. This suggests that smaller farms tend to overuse the land in comparison to their larger counterparts.

The considerable differences between the mean and median values are a result of a skewed distribution of shadow land prices towards smaller values. In light of this, we calculate the shadow values of total carbon sequestration using median values[3].

Table 4 and 5 present the estimated shadow values of total carbon sequestration. The values are calculated based on the median values of land shadow values and the total carbon sequestration in biomass—comprising the primary yield, secondary yield, and roots—for different crops (sourced from Kwiatkowski et al., 2020). Specifically, the shadow value of total carbon sequestration is determined by the ratio of the land shadow price to the total carbon sequestration for a given crop.

The results indicate that the shadow values of total carbon sequestration vary considerably across both crops and farm sizes. Differences across crops are primarily driven by variations in sequestration potential, while differences across farm sizes reflect variations in land shadow prices. Specifically, meadow hay exhibits the highest shadow value total carbon sequestration. By contrast, the lowest shadow values are for potato and sugar beet.

[3] Note: the use of mean values of land shadow prices will considerably increase the shadow values of total carbon sequestration.

Crop	Total carbon sequestration in biomass of primary yield, secondary yield, and roots (CO_2 t/ha a year)		Shadow values of total carbon sequestration (CZK t/ha)		
	Mean	Std.Dev	Point estimate	Interval estimate	
Winter wheat	16.6	2.77	154.87	132.73	185.89
Spring wheat	14.9	1.92	172.54	152.85	198.07
Spring barley	14.2	1.64	181.05	162.30	204.69
Winter rye	12.9	1.21	199.29	182.20	219.92
Oats	11.5	1.07	223.56	204.53	246.49
Maize	20.2	1.86	127.27	116.54	140.18
Winter oilseed rape	13	1.12	197.76	182.08	216.41
Potato	43.2	2.49	59.51	56.27	63.15
Sugar beet	80.4	3.75	31.98	30.55	33.54
Meadow hay	8.54	0.8	301.04	275.26	332.16

Source: Kwiatkowski et al. (2020); own calculations

Table 4: Shadow values of total carbon sequestration.

Crop	Shadow values of total carbon sequestration (CZK t/ha) - point estimate			
	0 - 99 ha	100 - 499 ha	500 - 999 ha	1000 and more ha
Winter wheat	57.55	25.98	222.77	481.20
Spring wheat	64.11	28.94	248.19	536.11
Spring barley	67.27	30.37	260.42	562.54
Winter rye	74.05	33.43	286.67	619.22
Oats	83.07	37.50	321.57	694.61
Maize	47.29	21.35	183.07	395.45
Winter oilseed rape	73.48	33.17	284.46	614.46
Potato	22.11	9.98	85.60	184.91
Sugar beet	11.88	5.36	46.00	99.35
Meadow hay	111.86	50.49	433.02	935.36

Source: own calculations based on Kwiatkowski et al. (2020) (Total carbon sequestration of different commodities – see also Table 4)

Table 5: Shadow values of total carbon sequestration according to the farm size.

In addition, the results suggest that larger farms tend to have higher shadow values of total carbon sequestration.

Conclusion

This study provides estimates of the shadow values of carbon sequestration based on the estimated land shadow prices. The aim is to contribute to the ongoing discussion on carbon sequestration by proposing a method for its economic valuation in agriculture. We suggest using a production approach to estimate the shadow prices of land, which can serve as the basis for calculating the shadow values of total carbon sequestration. Specifically, we apply a multiple outputs and inputs model of the transformation process, represented by an IDF, to estimate the shadow price of land. The resulting shadow price of land, together with the total amount of carbon sequestration, are then used to estimate the shadow values of total carbon sequestration. Finally, we present and compare the shadow values of total carbon sequestration across a selected group of crops and farm sizes.

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