8 HETEROGENEITY IN THE AGRICULTURAL SECTOR AND ITS IMPLICATIONS FOR MODELING VIABILITY

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Abstract

The paper investigates the viability of crop farms in Romania, an important topic because in rural regions agriculture is the main activity of a large part of the labour force and plays an important role in food security. In the literature, only trends and changes in viability as a result of policy at the European level are analysed. This study advances the literature by identifying the determinants of viability with a new model (correlated random effects ordered probit model) that intrinsically captures unobserved heterogeneity of farms. The results show that the viability of crop farms dependents incrementally on the volume of resources (scale). The paper shows that there is scope to increase farms' income if some changes are made in the structure of production factors (land, labor).

Keywords: Viability, Crop Farms, Correlated Random Effects Ordered Probit Model

JEL Classification: D22, C21, C51, Q12, Q18

1. Introduction

The structure of the Romanian agricultural sector is atypical in comparison to the other European countries. One tenth of the labor force works in the agricultural sector, and in the rural areas the percentage increase to 30% (the actual number is higher, but the new statisticalmethodology counts only farmers that sell at least 50% of their output), while the value added of the agricultural sector is less than 5% of the total. There are a large number of agricultural farms that have small plots of land and use mainly unpaid family workforce. Unfortunately, the majority of these farms are subsistence farms in the sense that the produced food is for family consumption. This is the reason for analyzing the viability of small and medium size crop farms (small farms have less than 10 ha; medium-scale farms have landholdings in the interval [10, 100] ha).

Although there is a large literature devoted to the viability of farms, there are very few papers that are modelling viability, most of them concentrating on analyzing the dynamics at different points in time, or trying to establish the effects of a change in policy at the European level.

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The novelty of our approach is the definition of viability on different time-horizons i.e. short term viability and long term viability, making the dependent variable a categorical one that takes three values. Another significant improvement on literature is the estimation method which is correlated random effects models for ordered probit function that capture unobserved heterogeneity, which has not been previously used in the literature in this context (for ordered probit response function).

2. Literature review

The concept of farm viability is important both from a food security aspect since family farms are the dominating unit of production in agriculture, supplying around 80% of the world food (FAO 2014), as well as from a living standard aspect, since, in a large number of countries, family farms and farms in general are the largest employer in rural regions. In our article, viability is defined in terms of ensuring a decent standard of living for agricultural farmers and their families.

In the literature there are several ways to measure viability. A first approach assesses viability with the help of indicators. There are numerous ratios considered, and although most authors agree that financial ratios are best in describing the viability of farms (Scott, 2001; Slavickiene and Savickiene, 2014), the choice between different indicators is very large, and authors disagree with respect to the "best" indicators. Example of such ratios are return on equity, expense to income, debt to income, subsidy to income, or profitability of sales, profitability of assets.

After choosing the financial ratios, typically, authors choose a threshold value for each considered ratio which helps to classify farms into viable or nonviable . This approach is helpful when the authors are interested into a comprehensive analysis of the financial situation of farms and identifying where their weaknesses are, but there is no unique indicator that establishes viability, and furthermore, the chosen cut out value is arbitrary. See Slavickiene and Savickiene (2014) for a comprehensive survey of papers employing this methodology and the relative usefulness of various ratios in assessing farms' viability.

Alternatively, authors compute a viability variable using data from the FADN. Spicka, *et al*. (2019) presents a survey of the most common farms viability measures. Using a measure of income, typically farm net income from which the authors deduct the opportunity cost of labor, sometimes the opportunity cost of capital and seldom the opportunity cost of land they arrive at a value which if it is positive the farm is viable or negative, and the reverse is true (Hanrahan, *et al*., 2014; O'Donoghue, *et al*., 2016; Vrolijk, *et al*., 2010; Koloszycz, 2020).

$$FNI - FAWU * w_r - K * r_K - L * r_L > 0$$

where:

FNI is the farm net income, or other measure of income, FAWU is the family (unpaid) annual working units,

w_r is the reference wage,
K is the operating capital of the farm,
r_K the cost of capital, rate of return on capital,
L is the size of the land,
r_L the rate of return on land.

Authors differ with respect to the reference cost they use in order to evaluate the opportunity cost of the factors. The reference wage can be the average wage in the economy in a region or across the country (O'Donoghue, et al., 2016; Vrolijk, et al., 2010), the average agricultural wage (Ryan, *et al*., 2016), the average wage from the FADN database (Numet and Omel, 2020; van Berkum, *et al.*, 2016), or a reference wage set by some decision makers[4] (Aggelopoulous, Samanthrakis and Theocharopoulos, 2007; Spicka, *et al*., (2019) argue that the average wage is a better measure for the reference wage in comparison to the average agricultural wage.

In the case of capital, some authors chose to use an arbitrary (typically 5%) rate of return on equity (Hanrahan, et al., 2014; van Berkum, et al., 2016; Ryan, et al., 2016). While this approach has its advantage since it offers a unitary treatment for the opportunity cost of capital especially in the case of multiple country analysis, Spicka, et al. (2019) argue that the 5% rate is too high in the context of decreased interest rates. Others authors choose to link the opportunity cost of capital to the interest rate of the government bonds (Vrolijk, *et al*., 2010), or to the long-term interest rate of the European Union Central Bank (Numet and Omel, 2020; O'Donoghue, *et al*., 2016).

The vast majority of papers analyse the trend in viability and/or sustainability of the agricultural holdings during an interval of time, and some concentrate on assessing the effect of a policy change, for example the effect that the removal or change in the criteria and value of the subsidies, might have on the farms. (O'Donoghue, *et al*. 2016; Vrolijk, *et al*. 2010; Numet and Omel, 2020; Coppola, *et al*., 2020). A comprehensive presentation of the studies and their finding is in (Poczta-Wajda, 2020).

A small part of articles aims to model the farm’s viability with the aim to identifying factors which are contributing toward increasing the viability (Singh, Bhullar and Joshi, 2009; Aggelopoulous, Samanthrakis and Theocharopoulos, 2007; Coppola, et al., 2020).

3. Data and Methodology

3.1. Data

Our analysis was conducted on the 2016-2018 FADN database of Romanian crop farms. The farms are very diverse, both in terms of size and characteristics. A large number of them are family farms, with plots of land as small as 0.4 hectares, at the other end are very large specialized farms whose arable land is over 500 hectares. The structure of the labor force is also very diverse, small farms (family farms) use mainly unpaid family work force, the average unpaid work force is 1 AWU per year, while the paid one is less than 0.1 AWU, while large farms use 10 AWU of paid labor force and 0.5 AWU unpaid labor force.

To reduce heterogeneity, we restricted our sample to small and medium sized farms.

We constructed a categorical variable which takes three values, 0 if the farm is non-viable, 1 if is viable on the short term, and 2 if the farm is viable on the long term. A farm is viable on short term if:

$$FNI > FAWU * w_r$$

The reference wage is the average agricultural wage for the AWU computed from the FADN database. We calculated the average for each year, and used the corresponding value in the formula (the average annual rate for the paid labour force is 5542 Euro in 2016, 5764 Euro in 2017 and 6216 Euro in 2018).

In the case of the long-term viability, the definition we employed is the following:

$$FNI > FAWU * w_r - +r_K * K - r_L * L$$

[4] *(Aggelopoulous, Samanthrakis and Theocharopoulos 2007) use as reference wage the reference income determined annually by the Greek Ministry of Agricultural Development.*

We selected the reference value for the return on capital and the return on land. The return on land was computed as the average rent per hectare taken from the FADN database, which is 106 Euro per hectare. The return on capital was computed as an average between the interest rate on Romanian government bonds and the Romanian stock exchange index, for the period 2016-2018 the value was 2.4%.

In Table we present the distribution of farms across viability. The difference between viability across farms' dimension is striking. Small farms are mostly non-viable but the percentage is slightly decreasing from 72.3% to 68.61% in 2017 and 64.17% in 2018, while medium size farms are mostly viable with an increasing trend (from 64.83% to 72.06% to 74.28%). There is only a small number of farms which are short term viable, farms are in general either long-term viable or non-viable.

Table 1. The distribution of viability across farms.

	Small farms		Medium farms	
	Freq.	Percent (%)	Freq.	Percent (%)
Non viable	993	68.44	834	29.49
2016	368	72.30	319	35.17
2017	317	68.61	264	27.94
2018	308	64.17	251	25.72
Short term viable	67	4.62	186	6.58
2016	25	4.91	66	7.28
2017	17	3.68	52	5.50
2018	25	5.21	68	6.97
Long term viable	391	26.95	1808	63.93
2016	116	22.79	522	57.55
2017	128	27.71	629	66.56
2018	147	30.63	657	67.32
Total	1451	100	2828	100

Note: Percentages are calculated relative to total farms of the category (small, medium). Source: Authors' compilations.

Table 2 presents the part of the dynamic information from the panel data with respect to the viability status of farms in all years.

Our dataset is unbalanced, so not all farms are defined for all periods of time. Considering all small farms (249) with data in both years (2016 and 2018), we have 61.04% of them non-viable in both time periods and 18.88% of them are upgraded from non-viable in 2016 to viable in 2018. We also have the opposite situation: 4.42% are downgraded from viable to non-viable, and 15.66% are viable in both periods. So, the proportion of small farms that are viable increases from four-to-one to two-to-one (0.53).

Out of the 517 medium farms for both years, 7.16% viable farms in 2016 downgraded to non-viable while 55.51% remain viable, and 21.28% upgraded from non-viable to viable in 2018.

Medium size farms from are split in approximatively one-to-two (1.68) proportion between non-viable and viable in 2016, but in 2018 the proportion changes to less than one-to- three (3.31). The increase in the number of viable farms is due to the fact that the percent of the viable farms becoming non-viable (7.16%) is less than the percent of non-viable farms becoming viable (21.28%).

Table 2. Viability dynamics for farms from 2016 to 2018 (in value and percentage)

		2018			2018 (%)		
		Non-viable	Viable	Total	Non-viable	Viable	Total
2016		*Small farms*					
	Non-viable	152	47	199	61.04	18.88	79.92
	Viable	11	39	50	4.42	15.66	20.08
	Total	163	86	249	65.46	34.54	100.00
		Medium farms					
	Non-viable	83	110	193	16.05	21.28	37.33
	Viable	37	287	324	7.16	55.51	62.67
	Total	120	397	517	23.21	76.79	100.00

Source: Authors' compilations.

3.2. Methodology

For each cross-sectional unit (farm) $i \in \{1,...,n\}$ and each time $t \in \{1,...,T\}$, we have (observed) data for the outcome variable y_{it} and the k_x -dimensional covariate vector x_{it}. A standard assumption is that the outcomes y_t are dependent across t conditional only on the observable x_t and heterogeneity c.

We consider a Correlated Random Effects (CRE) Ordered Probit model to account for unobserved heterogeneity. We follow Abrevaya and Hsu (2020) that introduced the concept of partial effects for a general nonlinear panel data model and in particular, calculate and estimate these effects for a correlated random effect probit model. We extend their approach for a CRE ordered probit model.

The dependent variable y is an ordered response taking on the values {0; 1; 2; ...; J} for some known integer J. The CRE ordered probit model for y (conditional on explanatory variables x_i and unobserved effect denoted by variable c_i) is derived from random effects probit model defined by Chamberlain (1980) as explained by Wooldridge.

$$y_{it}^{*} = x_{it}\beta + c_i + u_{it} \quad (1)$$

$$c \mid x,z \sim \text{Normal}(z\lambda_z, \sigma_c^2); \quad (2)$$

$$u_{it} \mid x_i, z_i, c_i \sim \text{Normal}(0; 1) \text{ for each time t} \quad (3)$$

where t denote the year t and x_t contains x_{it} for all cross-section unit (farm) i.

The relationship between the observed and latent variable is as follows:

$$y_{it} = 0 \text{ if } y_{it}^{*} < \alpha_1;$$

$y_{it} = j$ if $\alpha_j < y^*_{it} \leq \alpha_{j+1}$, $0 < j < J$;

$y_{it} = J$ if $y^*_{it} > \alpha_J$.

where $\alpha_1 < \alpha_2 < \cdots < \alpha_J$ are the model-determined cut points/threshold parameters.

We are interested in how changes in the elements of explanatory variables *x* affect the response probabilities, ceteris paribus $P(y_{it} = j|x)$, *j* = 0; 1; 2;..; *J*.

$$P(y_{it} = 0|x) = P(x_{it}\beta + c + u_t < \alpha_1|x) = \Phi(\alpha_1 - (x_{it}\beta + c)) \tag{4a}$$

$$P(y_{it} = j|x) = P(\alpha_j < x_{it}\beta + c + u_t \leq \alpha_{j+1}|x) = \Phi(\alpha_{j+1} - (x_{it}\beta + c)) - \Phi(\alpha_j - (x_{it}\beta + c)) \tag{4b}$$

$$P(y_{it} = J|x) = P(\alpha_J < x_{it}\beta + c + u_t|x) = 1 - \Phi(\alpha_J - (x_{it}\beta + c)) \tag{4c}$$

Our models are panel order probit that considers the discrete, ordinal nature of the viability rates. It assumes the existence of a normally distributed cross-section term c that capture the unobserved heterogeneity of farm that incorporates factors such as whether conditions (the level of rainfall, etc), management, quality of the factors involved in the production (land and labour force productivity, human capital characteristics of the owner), that could impact on viability but are not present in data set.

This heterogeneity is treated using a specification as described in Mundlak (1978) that include in the model the time averages of the independent variables and other time-invariant covariates. As we have T small and large N, we use pooled estimator, which is consistent and asymptotically normal with no additional assumptions on error term like weak exogeneity of the explanatory variables (Wooldridge, 2010).

We are interested in the partial effects[5] of some farm characteristics (database variables) that are known and represented in our database and in the presence of unobserved farm-specific heterogeneity that represents other characteristics that are not included in the database but are also important. From the perspective of a covariate, partial effects can be estimated averaged over the entire sample or at a value of interest. To account for heterogeneity, it is necessary to consider the partial effect on its unconditional distribution or on the conditional distribution given that value of interest (Abrevaya and Hsu, 2020).

These two different approaches leads to two different estimations of partial effects: average partial effects (APE) calculated as the population average of the partial effect when heterogeneity is treated as unconditional (see Abrevaya and Hsu, 2020; Wooldridge, 2019) and average local response (ALR) calculated as the population average of LAR (Local Average Response, as defined in Altonji and Matzkin, 2005) when heterogeneity is treated conditional on the variable value, respectively.

3.3. The Model

We estimated the model using a Correlated Random Effects (CRE) Ordered Probit model to account for unobserved heterogeneity, where the dependent variable is the viability defined above. We follow (Abrevaya & Yu-Chin, 2021) that introduced the concept of partial effects for a general nonlinear panel data model and in particular, calculate and estimate these effects for a correlated random effect binary probit model. We extend their approach for a CRE ordered probit model.

[5] *The partial effects on the response probabilities should be used for compare models.*

Among the independent variable we included are the three factors of production land, labour and capital. The factors of production should contribute positively to the viability of the farm, but if the farm uses too much of a factor, diminishing return can set in and the added revenue might not cover the additional costs, and we could be in the situation that the contribution of this factor is negative.

In order to assess whether being viable is an aleatory occurrence we introduce last year viability as an independent variable. We expect that farms which were viable in the previous year have a larger probability of being viable in the current year, if there are some characteristics of the farm that make it viable.

We introduced a variable capturing the productivity of the farm which is defined as output per input, the higher the variable the more productive the farm is. Because both output and input are expressed in monetary terms, the ratio captures some information regarding the relative prices (output vs input) as well.

We introduced long-term liability of the farm in order to capture the negative effect that borrowing to finance capital has on the profitability. Since capital and long-term liability are highly correlated, in the absence of the later variable, the effect would show through the former variable.

Next, we introduced variables pertaining to subsides like crops subsidies, decoupled subsidies and least favoured area subsidies (LFA) all variables are expressed as values per hectare. Since subsidies are an income paid to the farms, we expect the coefficient to be positive.

We use other inputs as well, inputs which are potentially important for farming, like fertilizers, crop protection and seeds, all computed per hectare. Fertilisers and crop protections were included to identify if there is evidence that their use helps crop farms to be viable. For seeds we introduced two variables, first the purchased seeds, and second own seeds which refer to seeds home grown. We introduce the two variables in order to check whether it is rewarding, in terms of increased production, for farmers to purchase seeds rather than use their own. If the coefficient of purchased seeds is positive and/or the coefficient of own seeds is negative, we can conclude that purchasing seeds is a better strategy for farmers.

The next group of variables refer to efforts of diversifying the farm either by diversifying the crops grown or pursuing other activities like animal husbandry. Most of articles identify diversification as a way to increase profitability and therefore viability of farms (Sanchez, *et al*., 2022; Ali, 2015; Birthal, Roy and Negi, 2015) so we expect that the variables included for farms that diversify would lead to increase probability of the farms being viable. There are several variables which capture different aspects of diversity. We included a direct measure of the number of crops cultivated. The expression is the follows:

$$div = 1 - \sum_i \left(\frac{l_i}{l}\right)^2$$

where l_i is the land occupied by the *i* crop and *l* is total land. The summation is an expression which measures integration of the farm. It is 1 if there is only one crop, and decreases towards 0 when there are a large number of crops cultivated. So, the measure of diversity is 0 for monocrop farms and tends to 1 with the increase in the number of crops. Another variable is a dummy included for farms that diversify their activity towards animal husbandry. And last, we included dummy variables for different crops in order to capture which are associated with higher probabilities of being profitable.

We included a variable which is an aggregate average of the yields of different crops. It is a standardised measure because one cannot directly compare yields of different crops, and in order to do so, we have computed average yields for each crop and year. For each farm for each year, we computed a weighted average of the ratio of crop yield to the average yield, and the weights are the share of the agricultural land dedicated to each crop in total agricultural land. We would expect that a higher yield is associated to a viable farm, so the coefficient should be positive.

We would have used as independent variables human capital characteristics like age, education, gender, number of family members as well as information regarding income from non-farming activity for the farmer and his/her family, but the database has no records on these topics.

4. Results

The coefficients (presented in Table 3) that are obtained are interpreted as the effect that the variable has on the probability of the farm being viable/non-viable. A positive coefficient means that increasing the variable by a unit increases the probability of the farm being viable, all else equal. For a negative coefficient the reverse is true. The magnitude to the increase can not be infer from the coefficients, only the direction of the change in probability (increase or decrease).

The specification of the model as an ordered probit is correct as indicated by the significance of the two cut values from the model's output. The choice for correcting heterogeneity was also correct, since several of the variables included to correct heterogeneity were significant.

Table 3. The results of the viability determinants of crop farms

	Coef.	St.Err.	t-value	p-value	Sig
Lag viability		.	.	.	
Short term viable	.232044	.143654	1.62	.106246	
Long term viable	.843259	.106818	7.89	0	***
Dummy for medium size farm	.994181	.15648	6.35	0	***
Productivity	2.05823	.415259	4.96	1.00e-06	***
Land	.046981	.00467	10.06	0	***
Labour	-.586277	.166939	-3.51	.000445	***
Capital	0	2.000e-06	-0.19	.851528	
Long term liability	-.000013	5.000e-06	-2.83	.00463	***
Decoupled subsidies/ha	.009137	.002018	4.53	6.00e-06	***
Crops subsidies/ha	.008667	.002518	3.44	.000578	***
LFA subsidies/ha	.010086	.003132	3.22	.00128	***
Fertilisers/ha	.000712	.001286	0.55	.579654	
Seeds/ha	.000168	.000692	0.24	.808393	
Own seeds/ha	-.003617	.003221	-1.12	.261565	
Crop protection/ha	.000511	.002312	0.22	.825204	
Contract work/ha	.002144	.001281	1.67	.094168	*
Diversity	.031256	.473568	0.07	.947378	
Aggregate price	-.00074	.001149	-0.64	.519706	
Yields	.16755	.062997	2.66	.007822	***
Dummy variables for types of crop					
Barley	-.012502	.109022	-0.11	.908701	
Corn	.338927	.171382	1.98	.047972	**
Rapeseed	.221078	.140673	1.57	.11605	
Sunflower	-.097322	.118313	-0.82	.410748	
Soy	-.069221	.226578	-0.31	.759982	
Wheat	-.155525	.149338	-1.04	.297678	
Dummy livestock	-.406266	.154612	-2.63	.008598	***
Cut1	5.201943	.709114			
Cut2	5.589617	.716387			

	Coef.	St.Err.	t-value	p-value	Sig
Mean dependent var	1.154661	SD dependent var		0.959939	
Pseudo r-squared	0.556468	Number of obs		1888.000000	
Chi-square	618.368986	Prob > chi2		0.000000	
Akaike crit. (AIC)	1536.727808	Bayesian crit. (BIC)		1824.978022	

*Note: *** p<.01, ** p<.05, * p<0.1*

Source: Authors' compilations

Error! Reference source not found. presents the marginal effects for the variable which were significant, separately for 2017 and 2018. As explained before there are two types of marginal effects, average partial effect which is computed relative to the average farm (what happens when the average farm shifted to a higher value), and average local response which is an average of the marginal effects for a farm relative to its observed value (what happens when the variable shifted to a higher value than the actual realization).

Marginal effects are computed for each viability group and indicates how will the probability of belonging to that group changes if the variable increase with one unit. Therefore, for variables with positive coefficients, the marginal effect of belonging to the non-viable group is negative[6], while the marginal effect of being short term viable and long term viable is positive. Since APE are the marginal effects computed for the average farm, it makes more sense to look at them rather than the average coefficient for each farm. As an observation we can notice that the modulus of the marginal effects are smaller in 2017 in comparison to 2018, which indicates that it was easier to be viable in 2018.

The results show that an important determinant of current viability is the previous period viability status. If the farm was previously long term viable, the probability of maintaining the status is higher. We consider that long term viability captures the effect of omitted variables (eg. management abilities of the farmer).

The productivity is another important variable for determining the viability status of the farm, this variable captures the effect of all relevant inputs.

Land is also a variable which has a positive influence on viability. An increase in land would benefit the farms in terms of the viability status. The strongest influence is on the non-viable farms, whose probability of being non-viable decreases, by the most amount. Moreover, medium size farm benefit in terms of increased probability of being viable, in comparison to the small farms, even more than strictly due to the additional land, as shown by the positive coefficient for the respective dummy variable.

When analysing labour, the situation changes, the variable has a negative influence on the probability that the farms is viable. It appears that, for the average farm, the number of average working units is too high. Again, the strongest effect is on increasing the probability of being non-viable. The capital, on the other hand has no significant influence on the viability status of the farm. The insignificance of the capital means that farms should contract out the agricultural work, since the coefficient for contract work is positive.

Long term liability is another variable which has a negative effect on the probability of a farm being viable. It is expected since it impacts the farm net income by decreasing it. More surprizing is that the positive effect of capital does not show up in the model. It might be due to the inconsistencies in measuring the values for the different components of capital (for details see Alexandri, *et al*., 2022)

[6] *The variable positively increases the probability of being viable, therefore decreasing the probability of being non-viable.*

The inputs related to specialized inputs (fertilizers, crop protection, seeds) have coefficients statistically insignificant. So we cannot quantify their effect on viability apart from their contribution coming through the productivity variable. All inputs are in monetary value, and therefore they include the effect of prices, beside the effect of quantity. Prices are influenced by the bargaining position of the farmer, since large farms can negotiate better prices if they buy their inputs in bulk. In the case of the crop protection costs, there are some questions regarding the consistency of the data (see Alexandri, *et al*. 2022)). Own seeds, which represent seeds home grown, are the only input that influences the viability status of the farms. The effect is to decrease the probability that the farms is viable. Which means that saving on seeds is not the correct approach with respect to being viable. As an observation, note that the marginal effects have the smallest values for the own seeds and subsidies variables, but note that we are comparing the effect of an increase of 1 ha in land to an increase of 1 Euro per ha in subsidies, for example, which are not necessarily comparable.

The subsidies variables, as expected, all have a positive influence on the viability status (Alexandri, Saman & Pauna, 2021). Surprisingly, it does not seem to matter very much under what form the subsidies are paid, decoupled, crop or LFA subsidies, the values for the three coefficients are quite close. However, this demonstrated the importance of subsidies for farms in least favoured areas.

The next included variables refer to the aspect of diversification. First, we tested whether animal husbandry might be a good strategy for farms to increase their viability. The dummy variable for diversified farms is significant but negative, therefore we find evidence that small and medium crop farms that diversify their activity with animal husbandry are decreasing their chances of being viable.

The dummy variables for specific crops do not show that some crops are very successful in promoting viability. Only in the case of corn there is evidence that it helps farms to be viable. The marginal effects for this variable is the second largest after productivity. This result is expected because corn is the most productive crop, especially in years with good weather.

Yields is also an important variable which determines the probability of being viable. This variable shows that farms that are very productive in terms of the efficiency are more likely to be viable. The marginal effect is the third largest.

Table 1. Marginal effects ALR and APE for the viability determinants

	ALR 2017			ALR 2018		
	Non Viable	ShortTerm Viable	LongTerm Viable	Non Viable	ShortTerm Viable	LongTerm Viable
Productivity	-0.008844	0.00386	0.004984	-0.011119	0.005392	0.005727
Land	-0.000231	0.000101	0.00013	-0.00029	0.000141	0.00015
Labour	0.00302	-0.001318	-0.001702	0.003797	-0.001841	-0.001956
Decoupled subs./ha	-0.000044	0.000019	0.000025	-0.000055	0.000027	0.000029
Crops subs./ha	-0.00004	0.000017	0.000023	-0.00005	0.000024	0.000026
LFA subs./ha	-0.000043	0.000019	0.000024	-0.000054	0.000026	0.000028
Own seeds	0.000027	-0.000012	-0.000015	0.000034	-0.000016	-0.000017
Yield	-0.000783	0.000342	0.000441	-0.000984	0.000477	0.000507
Dummy corn	-0.001108	0.000455	0.000653	0.001405	0.00067	0.000735
	APE 2017			APE 2018		
	nonViable	ST Viable	LT Viable	nonViable	ST Viable	LT Viable
Productivity	-0.001005	0.000739	0.000266	-0.002678	0.001877	0.000801
Land	-0.000026	0.000019	0.000007	-0.00007	0.000049	0.000021
Labour	0.000343	-0.000252	-0.000091	0.000915	-0.000641	-0.000274
Decoupled subs./ha	-0.000005	0.000004	0.000001	-0.000013	0.000009	0.000004
Crops subs./ha	-0.000005	0.000003	0.000001	-0.000012	0.000008	0.000004
LFA subs./ha	-0.000005	0.000004	0.000001	-0.000013	0.000009	0.000004
Own seeds	0.000003	-0.000002	-0.000001	0.000008	-0.000006	-0.000002
Yield	-0.000089	0.000065	0.000024	-0.000237	0.000166	0.000071
Dummy corn	-0.000145	0.000104	0.000039	-0.000379	0.000259	0.000115

Note: ST=short-time; LT=long-time

5. Conclusions

Small subsistence farms are especially non viable, and our paper find ways to change this aspect. Increasing the management ability of the farmers is one of the most important instrument in improving the performance of farms.

Another finding is that farms can increase their viability by changing the structure of the production factors: (i) increasing the land, by renting, because buying can be difficult for non-viable farms that have no access to credit and no liquidity, (ii) reducing labour force by increasing labour productivity, (iii) or by using contract work instead of investmenting in capital.

Apparently the most surprising result is that Romanian crop farms are not helped by diversification. The results show that neither increasing their number of crops nor diversifying into livestock farming contributes to promoting viability. However, this result could be a consequence of the climatic conditions of the specific years and the existing production structure. Indeed, 2016-2018 were good years for wheat and especially for corn, which are the top cereal crops in terms of both area and production.

There are also other instruments that farmers can use in order to become viable. An important factor that affects viability is the productivity. Farms with high productivity are more likely to be viable. Increasing the productivity means using better technology, accessing better markets . For small farms in order to achieve results would mean to form associations and let them negotiate on their behalf. There is still a large degree of uncertainty in agriculture due to weather variability, but the use of specialised seeds adapted to the type of land and climate specificities, as opposed to own seeds, can be an instrument in achieving viability.

Another important instrument for promoting viability of farms are subsidies. We found no evidence that some type of subsidies are more effective than others. However, the results show that targeted subsidies for disadvantaged areas (LFA) are very effective, as the marginal effect is of the same magnitude as for other subsidies.

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References

Abrevaya, J. and Yu-Chin, H., 2021. Partial effects in non-linear panel data models with correlated random effects. *The Econometrics Journal*, pp.519-535. https://doi.org/10.1093/ectj/utab004.

Aggelopoulos, S., Samathrakis, S . and Theocharopoulos, A., 2007. Modelling the determinants of the financial viability of farms. *Research Journal of Agriculture and Biological Sciences,* 3(6), pp.896-901.

Alexandri, C., Saman, C., Pauna, B. and Luca, L., 2022. Will Romanian Crop Farms be Affected Differently by Low Input Farming? *Agricultural Economics and Rural Development, New Series XiX,* pp.155-164.

Alexandri, C., Saman, C. and Pauna, B., 2021. Exploring The Relationship Between Farm Productivity And The CAP Subsidies For The NMS. *Romanian Journal of Economic Forecasting*, 24(4), pp.124-140.

Ali, J., 2015. Adoption of Diversification for Risk Management in Vegetable Cultivation. *International Journal of Vegetable Science, 21,* pp.9-20.

Altonji, J. and Matzkin, R., 2005. Cross Section and Panel Data Estimators for Nonseparable Models with Endogenous Regressors. *Econometrica*, 73(4), pp.1053-1102. https://doi.org/10.1111/j.1468-0262.2005.00609.x.

Birthal, P.S., Roy, D. and Negi, D.S., 2015. Assessing the Impact of Crop DIversification on Farm Poverty in India. *World Development 72,* pp.70-92.

Chamberlain, G., 1980. Analysis of Covariance with Qualitative Data. *Review of Economic Studies* 47, 225–238.

Coppola, A., Scardera, A. Anato, M. and Verneau, F., 2020. Income levels and farm economic viability in Italian farms: An analysis of FADN data. *Sustainability, 12, 4898*, pp.1-18.

FAO., 2014. The state of food and agriculture: Innovation in family farming. United Nations.

Hanrahan, K., Hennessy, T., Kinsella, A., Moran, B. and Thorne, F., 2014. Farm viability - A Teagasc National Farm Survey analysis. Teagasc National Rural Development Conference. Dublin.

Koloszycz, E., 2020. Economic viability of dairy farms in selected European Union countries. *Annals of the Polish Association of Agricultural and Agribusiness Economists,* XXVII(3), pp.128-140.

Mundlak, Y. 1978. On the Pooling of Time Series and Cross Section Data. *Econometrica,* 46, pp.69–85.

Numet, M. and Omel, R., 2020. Economic viability by farm size of Estonian family farms. *Problems of Agricultural Economics,* 1(362), pp.14-28.

O'Donoghue, C., Devisme, S., Ryan, M., Conneely, R., Gillespie, P. and Vrolijk, H., 2016. Farm economic sustainability in the European Union: A pilot study. *Studies in Agricultural Economics,* 118, pp.163-171.

Poczta-Wajda, A. 2020. Economic viability of family farms in Europe - a literature review. *Annals of the Polish Association of Agricultural and Agribusiness Economists*, XXII(4), pp.161-172.

Scott, J. 2001. The Nova Scotia Genuine Progress Index Soils and Agricultural Accounts. GPI Atlantic Canada.

Slavickiene, A. and Savickiene, J., 2014. Comparative analysis of farm economic viability assessment metodologies. *European Scientific Journal,* 10(7), pp.130-150.

Spicka, J., Hlavsa, T., Soukupova, K. and Stolbova, M., 2019. Approaches to estimation the farm-level economic viability and sustainability in agriculture, A literature review. *Agricultural Economics,* 65(6), pp.163-171.

Vrolijk, H., de Bont, C., Blokland, P. and Soboh, R., 2010. Farm viability in the European Union. Assessment of the impact of changes in farm payments. The Hague: LEI, part of Wageningen.

Wooldridge, J.M., 2010. *Econometric Analysis of Cross Section and Panel Data. London*: The MIT Press Cambridge, Massachusetts.

Wooldridge, J.M., 2019. Correlated random effects models with unbalanced panels. Journal of Econometrics, 211(1), pp.137-150. https://doi.org/10.1016/j.jeconom.2018.12.010.