Exploring the factors that influence the market value of small farms in Romania*

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Abstract

The study aims to analyse factors that influence the market value of small farms in Romania. The research methodology involved a Gibbs sampling and updates of the Metropolis-Hastings algorithm. Findings demonstrate distinction in the estimated market values of small farms and their features across households and explain the role and influence of socio-economic, institutional, and marketing factors. The impact of the independent variables shows that the level of education, support for agri-environmental activities, unfavourable areas and sales to processing plants, have positively influenced the estimated market value of small farms.

Keywords: market value, marketing channels, Bayesian analysis, agri-food marketing
JEL Classification: C11, D30, Q13

Introduction

Globalisation, demographic change, market liberalisation, information technology, climate change, and economic crises are affecting the work of small farmers around the world. The specialised literature in the field addresses the importance of trade for the development of agriculture and economy, the role of agriculture in the economic development of Romania, the importance of marketing and agricultural reforms for the activity of small farmers, and the role of institutions and financial measures in improving the lives of those living in rural areas.

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A relatively small body of literature has documented aspects related to small farms with Bayesian analysis in general, and Gibbs sampling as an update of the Metropolis-Hastings algorithm, respectively. Balcombe and Tiffin (2010) discovered a reversible jump approach to the Bayesian Model Averaging for the Probit model with uncertain regressors in their research for Organic Production and Computer Usage among UK farmers. Holloway et al. (2002) emphasised two Bayesian models that were tested during the last twenty years to implement truncated and discrete-choice data, namely, the spatially autoregressive Probit (SARP) model and Markov-chain Monte Carlo method (MCMC) using normal data and outline the Gibbs sampling algorithm.

This study aims to provide a one at a time and in a particular order method to the Metropolis-Hastings sampling algorithm and Gibbs sampling as an update algorithm. This aspect represents a novelty that can bring additional value to the literature.

The present study analyses the main factors of market value of small farms by adopting a Bayesian approach to a selected survey dataset from all historical regions of Romania. Many agricultural economists investigate small farm production and commonly emphasise market prices, farmer education, distribution channels, marketing channels and related socio-economic factors thought to influence on-farm outputs. In our scientific approach, we attempt to estimate the market value of small farms in Romania based on four pillars: socio-economic factors, agricultural support and investment, marketing forces and marketing channels. However, it is noted that some authors analyse agricultural production using a Bayesian analysis with a design matrix that incorporates all data from the explanatory variables, (i.e. the factors that may influence crop), a vector of regression coefficients which measures how much of the variation of crop yield is accounted for by the explanatory variables, and independent Gaussian noise terms (Wang et al., 2019). Moreover, we found that some authors (Moglia et al. 2018) outline a Bayesian Network model for exploring the relative likelihood of technology implementation concerning a specific category of crop (i.e. rice-based agricultural systems) as well as the influence of diverse sensitivities of technology. Additionally, some authors pointed out that the mean output of a specific farmer can be assessed with a Bayesian Stochastic Frontier Model (Chakuri et al. 2022), which implies some errors of measurement, and a non-negative error term that represents the technical inefficiency (i.e. the quantity by which the firms output decrees).

1. Literature review

Farmers living far from road infrastructure and agri-food markets tend to market a smaller share of their production. On the other hand, changes in consumer behaviour and new technologies have led to an increase in the role of supermarkets and food-processing industries in the distribution of agri-food products from small farms. In 2019, the trade of food retailers in Romania exceeded a record level of 100 billion lei (over 21 billion euros). Small farmers are affected by such changes and need to adapt to these growing markets, as supermarket chains require certain distribution chains to ensure the consistency of agri-food supply at certain food quality and safety standards. According to Ouma et al. (2010), smallholder farmers do not have reliable information on the market and marketing channels. Some small farm owners are constrained by insufficient marketing information on price and their level of education (Mmbando/Baiyegunghi 2016). For small farmers and processors, an alternative to this would be the individual and direct approach to niche markets through cost management or a differentiation strategy. There is no unanimously accepted international or European definition for small farms. Also, the concept of subsistence farms has different approaches in the literature. Two important criteria are used to delimit farms according to their size: standard output or utilized agricultural area. To implement the measures imposed by European policies, Romania has provided in its regulations the definition according to which subsistence farms have an economic size between 2 and 8 ESU (European Size Unit). According to data provided by the National Agency for Rural Development in 2022, there are 3.140.000 farms in Romania with an average surface area of 2 ha for those between 2 and 4 ESU and an average area of 3 ha for those between 4 and 8 ESU. For a more detailed discussion of the definition of small and semi-subsistence farms, see Fritzsch et al. (2008).

According to European Commission Data available on the Eurostat platform, there were 9.1 million agricultural holdings in the EU in 2020, of which 2.9 million holdings (the equivalent of 31.8 %) were located in Romania. Almost two-thirds of the EU's farms were less than 5 hectares (ha) in size in 2020.

Romania is the Member State with the highest number of farms; nine in every ten farms (90.3 % or 2.6 million farms) were smaller than 5 ha, but 0.9 % of farms of 50 ha or more in size farmed a little over one-half (54.0 %) of all the utilized agricultural area (i.e. UAA), in the country. Small farms of under 5 ha were also typical in Malta (96.6 % of the total), Cyprus (87.5 %), Greece (74.0 %), Portugal (73.4 %), Croatia (70.6 %), Hungary (64.9 %) and Bulgaria (64.0 %), as well as in some regions of Southern Poland and coastal regions of Spain and Italy.

The market value of small farms varies depending on their size and type of farming activities. Small farms can enhance market participation through innovations and niche markets, but face challenges due to globalisation favouring larger operations and market concentration by large companies (Werbrouck/Bresnyan 2012).

According to Pingali et al. (2019), smallholder farmers play a significant role in the agricultural sector, contributing to food production and rural economies. Here, the market value of small farms is also influenced by market infrastructure and costs.

Factors influencing the market value of small farms include socio-economic aspects like age, gender, education level, and household size; institutional factors such as access to credit and extension services; market factors like prices and transport, and external factors like natural calamities affecting crop yields (Galli et. al 2018).

Market access, reduced transaction costs, improved market infrastructure, and limiting intermediary influence are essential for small farms to effectively link to value chains and new marketing platforms, enhancing their market value and participation in commercial production (Rapsomanikis 2015).

2. Research Methodology

The primary data were collected based on a survey conducted on a sample of 900 small farms in Romania distributed over the 5 historical geographical areas: Transylvania, Oltenia, Muntenia, Moldova, and Banat. The survey was conducted between June and October 2019 by holding structured face-to-face interviews with representatives of small farms from the different geographical regions of Romania mentioned above. Interviewers were appointed as data collectors for the County Directorates for Agriculture. From the total of 900 questionnaires, 887 were validated. A purposeful and random selection of the research sample was used. In the first stage, small farms were selected. The first criteria adopted for the selection of farms were the utilized agricultural area (i.e. UAA – ha), up to 20 ha, and standard output (i.e. SO – thousand EUR) 15.000 euro. The lower limit (15,000 instead of 50,000) was chosen for several reasons: first, the high level of fragmentation of the agrarian structure. Second, according to the Romanian National Institute of Statistics 3.053.088 farms (91,58 %) had a UAA under 5 ha; 3.188.660 farms (93,18 %) had a SO up to 8.000 euro and only 114.168 farms (3,34 %) achieved up to 15.000 euros in 2016. These criteria of small farms are most often met by family farms While this is a very heterogeneous group, it also is the most frequent type of farm in Romania. Family farms, apart from owning agricultural land and running agricultural activities, are characterized by agricultural work using the labour force of the farm, i.e. family members. Analysing the structure of small farms based on age as a socioeconomic variable (i.e., SE1), there are 4 frequency ranges (i.e., 4 quantiles of SE1). The most significant frequency (i.e., 243 farms) is farmers who are between 23 and 38 years old. The lowest frequency (i.e., 205 farms) is farmers aged between 39 and 47 years. The minimum age is 23 years, the maximum is 77 years, and the average is 47 years (Table 2).

Regarding education as a socio-economic variable (i.e., SE2), the following levels were considered in the survey questionnaire: level 1 – no education, level 2 – primary, level 3 – secondary, level 4 – vocational, level 5 – general, level 6 – bachelor's degree and level 7 – master's degree. From the analysis of the structure of small farms according to SE2, it can be observed that 45 % of farmers have level 5 studies – general, and approximately 20 % of farmers have level 4 studies – vocational. Approximately 17 % of farmers have a level 6 bachelor's degree (Table 1).

Related to the socio-economic variable number of household members (i.e. SE3), it is noted that the most significant share is given by households with 3 members or approx. 34 %, which translated in absolute sizes represent 304 small farms, followed by households with 2 members at approx. 26 % (i.e. 231 small farms), and those with 4 members, approx. 24 % (i.e. 214 small farms) (see Table 1).

Table 1. The structutttre of small farms according to all variables

Variables	N / Freq.	Min / Per cent	Max /Cum.
SE1 Age (4 quantiles of SE1)			
1	243	23	38
2	205	39	47
3	229	48	56
4	210	57	77
Total	887	23	77
SE2 Education (from level 1 to 7)			
1	1	0.11	0.11
2	11	1.24	1.35
3	128	14.43	15.78
4	177	19.95	35.74
5	400	45.10	80.83
6	146	16.46	97.29
7	24	2.71	100.00
Total	887	100.00	
SE3 Number of household members			
1	48	5.41	5.42
2	231	26.04	31.45
3	304	34.27	65.73
4	214	24.13	89.85
5	69	7.78	97.63
6	16	1.80	99.44
7	3	0.34	99.77
8	1	0.11	99.89
9	1	0.11	100.00
Total	887	100.00	

Variables	N / Freq.	Min / Per cent	Max /Cum.
ASI1 – Direct payments (%)			
<79	62	6.99	6.99
80	30	3.38	10.37
90	30	3.38	13.75
91–97	27	3.04	16.80
100	738	83.20	100.00
Total	887	100.00	
ASI2 – Support for Agri-env. & LFA*			
0	820	92.45	92.45
1	67	7.55	100
Total	887	100.00	
BEMVF (4 quantiles)			
1	223	0	
2	221	51,400	51.3
3	222	88,676	88.5
4	221	191,000	190.0
Total	887	0	1,250.0

Note: * true = 1 false = 0;

Related to the type of agricultural support instruments (i.e. ASI) that farmers are using, our database included the following 5 types: i) Direct payments; ii) Capital subsidies; iii) Support for Agri-environmental activities and LFA; iv) Organic farming; v) Other subsidies (e.g. State aid, "Minimis" State aid, etc.).

After several statistical estimation tests, we decided to use only the following types of ASI, as follows:

1. Direct payments (i.e. ASI1), (e.g. payments for production, payments for agricultural area -%);
2. Support for Agri-environmental activities and LFA (i.e. less favourable areas), excluding organic farming (i.e. ASI2);

The estimated market value of the farm (i.e. BEMVF)- The estimated market value of the farm was established by the respondents to the selected questionnaires (i.e., owners of farms). For the assessment, the established criteria considered the following assets: Land (with forest); Capital assets (e.g. building, machinery, equipment), and Livestock. Farmers specified, according to criteria outlined before and the average values in the last 3–5 years, the estimated share of a given form of financial support in total support.

The structure of small farms according to ASI1 is as follows: approximately 83 % of the farms received 100 % financial support in the form of direct payments (i.e., 738 farms), approx. 7 % benefited from financial support less than 79 % (i.e., 62 farms), and approximately 3 % of farms received support between 91 and 97 %.

The structure of farms considering Support for Agri-environmental activities and LFA – ASI2 – needs to be highlighted: approximately 92 % of the total farms (i.e., 820 farms) obtained this type of financial support, and approx. 8 % (i.e., 67 farms) did not benefit from this type of financial support.

The structure of small farms according to the socio-economic variable estimated market value of the farm (i.e. BEMVF) shows that the average value is about 140 thousand lei (i.e. about 31,000 euros in 2020), and the maximum value attributed by farmers is 1,250 thousand lei (i.e. about 278,000)

Table 2. Descriptive statistics of variables

Variable	Obs.	Mean	Std. Err.	[95 % Conf. Interval]	SD	Variance
BEMVF Estimated market value of the farm (Lei)						
	887	139,178.8	4,487.7	130,371–147,986	133,653.8	17.90 mil.
SE1 Age of farmer (owner of the farm)						
	887	46,743	.4043	45,949 – 47,536	12,042	145,004
SE2 Education (from level 1 to 7)						
	887	4,688	.0348	4,619 – 4,756	1,039	1,080
SE3 Number of household members						
	887	3.103	.0382	3.027 – 3.177	1,140	1,300
ASI1 Direct payments						
	887	95,136	.5077	94,139 – 96,132	15,121	228,634
ASI2 Support for Agri-environmental Activities and LFA						
	887	.0755	.0088	.0581 –.0929	.2644	.0699
MF1 Distance between the farm and the nearest city						
	887	27,235	.7593	25,743 – 28,725	22.6128	511.34
MF2 Difference in sales prices for distribution channels						
	887	.1928	.0133	.1668 –.2188	.3947	.1558
Log (MC1) Sale on the street markets, marketplace and bazaar						
	887	.5614	.0167	.5287 –.5942	.4965	.2465
MC2 Sale to processing plants						
	887	.4555	.0167	.4226 –.4883	.4983	.2483
MC3 Sale directly from the farm to neighbours and tourists by the roadside						
	887	.1939	.0133	.1678 –.2199	.3956	.1565
MC4 Sale at trade fairs						
	887	.2638	.0148	.2348 –.2929	.4409	.1944

The type of variables presented in Table 2 are based on data provided by farmers in the section of basic information (i.e. MF1) and the relationship between farming and the market (e.g. MF2, MC2, MC3, MC4 – dummy explanatory variable, and MC1 quantitative explanatory variable).

In connection with the structure of farms, MF1 shows that the mean distance between a farm and the nearest city is about 27 km. Most farms (i.e., 238 farms) are located in the first quantile, and the distance is between 0 and 10 km. The farms included in quantile 4 (i.e., 220 farms) are located at a distance between 37 and 106 km.

Concerning the structure of farms by MF2, the difference in sales prices for distribution channels is highlighted as follows: approximately 81 % of the farms (i.e., 716 farms) did not see any difference in sales prices when they used different distribution channels, and approx. 19 % (i.e., 171 farms) found that there was a difference.

Associated with MC1*,* most of the farmers (i.e., 442 farmers) registered a difference in price sales between 11 % and 100 %, 65 farmers registered differences between 0.5 % and 10 %, and 380 farmers did not register any differences.

With variable MC2 it can be seen that almost 54 % of small farms (i.e., 483) chose to sell to processing plants but nearly 46 % of them (i.e., 404) did not use this promotion technique.

Related to variable MC3 it is shown that almost 19 % of farms (i.e., 173 in absolute units) chose to sell directly from the farm to neighbours or tourists by the roadside. However, nearly 81 % of farms (i.e., 714) did not use this advertising technique.

Regarding variable MC4 it could be illustrated that just about 26 % of farms (i.e., 234 in absolute units) chose to sell to processing plants, and approximately 74 % (i.e., 653) did not use this promotion technique.

Because some variables show high values for SD compared to the reported mean, logarithm values were used in the regression model for some of them (see equation number 8). In the table below, data were extracted from STATA median values for all variables (except dichotomous variables).

Table 3. Median values of variables

Variable	Obs.	Percentile	Centile	[95 % Conf. Interval]
BEMVF Estimated market value of the farm (Lei)				
	887	50	88,572	82,097–98,674.73
SE1 Age of farmer (owner of the farm)				
	887	50	47	46–48
SE2 Education (from level 1 to 7)				
	887	50	5	4–5
SE3 Number of household members				
	887	50	3	2–3
ASI1 Direct payments				
	887	50	96	95–100
MF1 Distance between the farm and the nearest city				
	887	50	21	20–24

By using our econometric model, we wanted to highlight the fact that socio-economic factors, agricultural support and investment, marketing forces and marketing channels can increase the market value of small farms in Romania.

The farmer's age (farm owner) was measured on a proportional scale using an open-ended question. According to Amaya and Alwang (2011), older farmers tend to choose nearby markets to sell their products. As they get older, farmers lose interest in long-distance markets, which require greater financial and time resources. There is a positive link between the age of the farmer and the decision to sell through informal markets (Shiimi et al. 2012).

In Romania, according to a study by Mortan et al. (2016), an advanced age of the farmer reduces their concern about developing the farm and implicitly identifying distribution channels for the products derived from it. This finding must be put in the context of the ageing population living in rural areas in Romania.

Education influences the costs and time required to process information (Bywaters/Mlodkowsk 2012). Mutura et al. (2015) show that in the case of small dairy farms in Kenya, farmers with a high level of education tend to sell their products through cooperatives because they understand and access market information. Also, according to the results of a study by Farmer and Betz (2016), farmers in West Virginia with a higher level of education choose to sell agri-food products directly to end consumers, which means that they have been informed and they took the risk of choosing direct marketing channels. The influence of the farmer's education level on marketing channel selection represents a major factor since farm operators with higher levels of education commonly show reduced wholesale market participation (Gong et al. 2006; Liao et al. 2017).

In the case of small farms in Romania, a direct link has been identified between the farmer's level of education and the intention to develop the farm (Mortan et al. 2016).

The number of household members was measured on a proportional scale through an open-ended question.

According to various studies, this variable influences the amount of agricultural production for sale. Monson et al. (2008) showed that small farms with more members in their households offer a smaller amount of production for sale through direct marketing channels. Even if a large number of members of the household can provide the labour needed to obtain a larger quantity of production, the products will be distributed directly to the nearest market if there is no possibility of storage or transport.

Distance from the farm to the nearest town was measured on a proportional scale using an open-ended question, representing the number of kilometres to the nearest main market in the neighbouring town.

The depended variable it is represented by the estimated market value of the farm (i.e., BEMVF). Existing literature describes several methods to estimate the value of a farm. The most common method is the "patrimonial" method (Jeanneaux et al. 2017). This method considers the market value of the various assets that the farm has. Nevertheless, it also considers socio-economic factors, for example.

In our study, we tried to adapt economic findings to situations where the socio-economic factors of the farmers influence the value of small farms.

3. Method

Bayesian analysis is common in various areas of interest, but its utilisation in science and engineering is predominant. More precisely, Bayesian statistical inference is practised in econometrics (Poirier 1995; Chernozhukov/Hong 2003; Kim et al. 1998) and several other fields. Additionally, it is a powerful tool for making inferences from data. One of the most significant discoveries was the implementation of the random-walk Metropolis algorithm (Metropolis et al. 1953) to clarify issues in statistical physics, and the Gibbs sampling algorithm (Geman/Geman 1984), which was first used in image processing.

The development of the Markov chain Monte Carlo (i.e., MCMC) method was the result of these ideas. It became an integral part of statistical practice. Various specialised techniques were introduced that utilise MCMC. Some of these include the reversible-jump MCMC (Green 1995) or the perfect sampling algorithm (Propp/ Wilson 1996). Due to the complexity of the task involved in performing Bayesian analysis, finding ways to minimise the number of integrals is often difficult. In most cases, the analysis is performed through simulations. The integrals elaborated in Bayesian inference, for some functions of the random vector (i.e., θ), given the observed data (i.e., y) are as follows:

$$B\{g(\theta)\} = \int g(\theta)p(\theta | y)d\theta \tag{1}$$

In contrast to deterministic algorithms used in frequentist statistics (a.n., treat parameters as fixed values and rely on hypothesis testing and confidence intervals), MCMC methods like the Metropolis-Hastings algorithm (i.e., MH) and Gibbs sampling offer a powerful way to explore complex, high-dimensional parameter spaces (Chib 2001, Luengo et al 2020) and generate samples from the posterior distribution (Spall 2003). This iterative process converges to the true distribution, enabling practitioners to obtain estimates and quantify uncertainty in a wide range of models.

An additional MCMC method that can be considered a special case is the use of the Gibbs sampling method (Gelfand et al. 1990). This is the technique used in our regression model using STATA17, where the updates are the complete conditional distributions of the various parameters. Consequently, if $\theta = \left(\theta^1,\ \ldots\theta^d\right)$ and, for $j = 1\ldots,\ d,\ q_j$ is the conditional form of θ^j given the rest $\theta^{\{-j\}}$; follow by Gibbs update along this way: for $t = 1, \ldots, T-1$, T (i.e. T represent the size of the MCMC sample – iterations that are retained, in our study $T_0 = 3000$ and T=30000) and for $j = 1\ldots,\ d$:

$$\theta_t^j \sim q_j\left(\bullet \,\middle|\, \theta_{t-1}^{\{-j\}}\right) \tag{2}$$

The original Gibbs sampling method updates the model parameters one at a time according to the full conditional distribution of the algorithm. This method has various advantages, such as its high efficiency and the ability to accept all proposals. Although the full conditionals are usually not available in most cases, they can be easily obtained through a hybrid MH algorithm that only updates the various blocks of parameters (i.e., the random-walk updates of the Gaussian random-walk method with the Gibbs updates). The combination of the two methods allows the algorithm to improve the mixing of the chains.

At the level of our study, it was assumed that all the data are normally distributed with a known mean, then the algorithm can specify an inverse-gamma before the model parameters, in this way:

$$y \sim N(\mu, Cov\{g(\theta)\}), Cov\{g(\theta)\} \sim InvGamma(\alpha,\ \beta) \tag{3}$$

where $y = (y_1,\ y_2, \ldots y_n)$ is a data sample of size n (in our study n=887) with a mean μ; α and β are hyperparameters (i.e. prior shape and prior scale) of an inverse-gamma prior distribution for the variance of a normal distribution of y_n.

In this case, the conditional distribution is an inverse-gamma prior, but with different scale and shape parameters. This allows the algorithm to set up a separate block for the updates:

$$Cov\{g(\theta)\} \sim InvGamma\left(\widetilde{\alpha} = \ \alpha + \frac{n}{2}, \widetilde{\beta} = \beta + \frac{1}{2}\sum_{i=1}^{n}(y_i - \mu)^2\right) \tag{4}$$

The initial MH algorithm updates the model parameters simultaneously. This method may result in poor mixing for high-dimensional models since the chain may remain in the posterior distribution for a long time. This issue can also be caused by the varying scales of the model parameters. An effective solution is to separate the model parameters into two or more subsets (i.e., blocking). This method allows the algorithm to update the model parameters in a separate order.

To confirm the hypotheses of our research, we used the data set on small farms that we examined earlier. We predicted the market value of small farms (i.e., log variable) from the farmer's age, farmer's level of education status, farmer's number of household members, whether or not the farmer uses direct payments, whether or not the farmer's benefits support Agri-environmental activities and LFA, the distance between the farms and the nearest city (i.e., log variable), farmer's difference in sales prices for distribution channels, the farmer's sale on the street markets, marketplaces, bazaar (i.e., log variable), farmer's selected sale to processing plants, whether or not the farmer adopted sale directly from the farm to neighbours s or tourists by the roadside, and the farmer's choice to sell at trade fairs. We set up the model as follows:

$$Log(B_{EVMF,\,i}) = \alpha + \beta_1 x_{SE1,\,i} + \beta_2 x_{SE2,\,i} + \beta_3 x_{SE3,\,i} + \\ \beta_4 x_{ASI1,\,i} + \beta_5 x_{ASI2,\,i} + \beta_6 \log(x_{MF1,\,i}) + \beta_7 x_{MF2,\,i} + \\ \beta_8 \log(x_{MC1,\,i}) + \beta_9 x_{MC2,\,i} + \beta_{10} x_{MC3,\,i} + \beta_{11} x_{MC4,\,i} + \epsilon_i \\ ,\ i = 1, \ldots n \qquad (5)$$

All scalar parameters maintained on the entire real line, for example, regression coefficients and log-transformed positive parameters, are allocated a normal distribution with zero mean and variance 2 prior, where prior is given by the option in STATA17. The default priors' value in case of normal prior for coefficients. The standard deviation is 100 (set in STATA17 "Priors" tab section), and thus the default priors for these parameters are $N(0; 10000)$. In our study we set the MCMC number of 33,000 iterations; Burn-in by 3,000 and the sample size N= 30,000; maximum block size is set by default at 50; These priors are justly vague for parameters of moderate size but may become revealing for large-scale parameters.

All positive scalar parameters are allocated an inverse-gamma prior to the shape parameter α and scale parameter β, $InvGamma(\alpha; \beta)$. The default values for α and β are 0.01, and thus the default prior for these parameters is $InvGamma(0.01,\ 0.01)$. Related to adaptive MCMC procedure the default values are as follows: adaptation interval =100; the maximum number of adaptive iterations = 25; minimum number of adaptive iterations = 5; parameter controlling acceptance rate, α = 0.75 parameter controlling proposal covariance, rate, β = 0.8; tolerance for acceptance rate = 0.01; initial multiplier for the scale factor for all blocks=2.38

4. Results and discussions

The prior distribution for all the regression parameters is a normal distribution with a mean equal to zero and variance equal to 10,000; prior to sigma2 parameter is presented as follows:

Table 3. Bayesian linear regression-Gibbs sampling statistics

Parameters	Values
MCMC iterations	33,000
Burn-in	3,000
MCMC sample size	30,000
Number of obs.	451
Acceptance rate	1
Efficiency: min.	.961
avg.	.997
max	1
Log marginal likelihood	-492,836

Source: *Authors' processing in STATA17*

MCMC iteration is a total of 33,000; the first 3,000 iterations are burn-in and are discarded; the number of iterations retained in the MCMC is 30,000; the number of observations and data sets is 471.

In our model, the acceptance rate is 1 which means that 100 % out of 30,000 proposal parameter values were accepted by the algorithm. The minimum efficiency for the model parameters is.961, the average efficiency is.997, and the maximum efficiency is 1.

After we establish the Bayesian regression model selector (i.e., continuous outcomes / linear regression) and picked, in STATA17, all the criteria and values presented previously we registered the following model:

$$\begin{aligned} Log(\widehat{B_{EVMF}}) &= 12.396 - .0035x_{SE1} + .0265x_{SE2} + .0717x_{SE3} - \\ &.0079x_{ASI1} + .2047x_{ASI2} + .0523\log(x_{MF1}) + .4533x_{MF2} - \\ &.2367\log(x_{MC1}) + .4046x_{MC2} + .1236x_{MC3} + .3123x_{MC4} \end{aligned} \tag{6}$$

Analysing the sign of beta specific for all independent variables, it is noted that, excepting {Log (BEMVF): Log (MC1)}, {Log (BEMVF): ASI1}, and {Log (BEMVF): SE1}, most parameters positively influence the value of {Log (BEMVF)}. Nonetheless, if we consider the value of intercept and sigma2 (i.e., +.3372) we notice that, in the end, all parameters have a positive influence on {Log (BEMVF)}.

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Table 4. Posterior summary statistics

Parameters	Mean	SD	MCSE	Median	[95 % Conf. Interval]	
Log (BEMVF)						
SE1	-.0035	.0025	.00002	-.0035	-.0085	.0014
SE2	.0265	.0299	.00017	.0262	-.0319	.0857
SE3	.0717	.0241	.00014	.0717	.0242	.1191
ASI1	-.0079	.0022	.00001	-.0078	-.0121	-.0034
ASI2	.2047	.1232	.00071	.2040	-.0359	.4471
Log (MF1)	.0523	.0349	.00020	.0523	-.0156	.1198
MF2	.4533	.0737	.00043	.4535	.3083	.5976
Log (MC1)	-.2367	.0373	.00021	-.2364	-.3096	-.1642
MC2	.4046	.0684	.00039	.4042	.2706	.5392
MC3	.1236	.0853	.00049	.1233	-.0425	.2904
MC4	.3123	.0736	.00043	.3121	.1673	.4569
Intercept	12,396	.3675	.00212	12,396	11,679	13,112
sigma2	.3372	.0228	.00014	.3361	.2952	.3847

Source: *Authors' processing in STATA17*

Generally, the posterior mean estimates of all parameters, except sigma2, are close to the OLS estimate of variables

Posterior standard deviations are between 0.022 (i.e., {Log(BEMVF): ASI1}) and 0.3675 (i.e., {Log(BEMVF): cons}), and they are close to the standard error of the OLS estimate (i.e., Appendix no. 1).

The standard error estimates of the posterior means, MCSEs, are low for all parameters. For instance, MCSE is 0.0043 for {Log(BEMVF): MF2}. This illustrates that the accuracy of our estimate is, up to two decimal points, 0.45 defining that MCMC converged.

The posterior means and medians of {Log(BEMVF)} and all parameters are close, including for sigma2, which suggests that the posterior distribution for {Log(BEMVF)} and all predictor variables may be symmetric.

According to the credible intervals, we are 95 % certain that the posterior mean of all parameters is approximately between equal-tailed 95 % conf. intervals. For example, the posterior mean of {Log(BEMVF): cons} is between 11.7 and 13.11, and the posterior mean of {sigma2} is practically between.30 and.38. We can conclude from this that {Log(BEMVF): cons} is greater than 12 and that {sigma2} is greater than.31, with a very high probability.

A *cumulative sum* (i.e., cusum) plot is used to measure the variation in the mean and the sample values against the iteration number (Yu and Mykland, 1998).

By inspecting cumulative sum plots for all parameters, it can be seen:

1. Socio-economic and ASI variables show (Figure 1) that there is no contrast between the jagged lines of the fast mixing parameters. However, in the case of {Log(BEMVF): SE3} along with {Log(BEMVF): ASI1}, after the first nearly 15,000 iterations, the cusum curve stays in the negative y plane and by the end, it recovers and crosses the x-axis several times. The opposite situation is registered by {Log(BEMVF): Log(ASI2)} during the first nearly 20,000 iterations. The curve stays in the positive y plane and by the end, it recovers and crosses the x-axis several times.

Overall, during the total 30,000 iterations, it seems that all parameters registered a well-mixing chain, and in exceptional ways age and education.

2. In Figure 2, sum plots for market forces variables indicate that there is no dissimilarity among the jagged lines of the fast-combining parameters. However, in the case of {Log(BEMVF): Log(MF1)}, during all iterations, the cusum curve tends to stay more in the positive y plane and by the end crosses the x-axis numerous times. The contradictory situation is registered by {Log(BEMVF): MF2} during the first approximately 20,000 iterations. Here, the curve stays in the negative y plane and by the end, it recovers and crosses the x-axis frequently. Globally, during all iterations, it seems that both parameters recorded a well-mixing chain.

Figure 1. Cusum of socio-economic and ASI variables

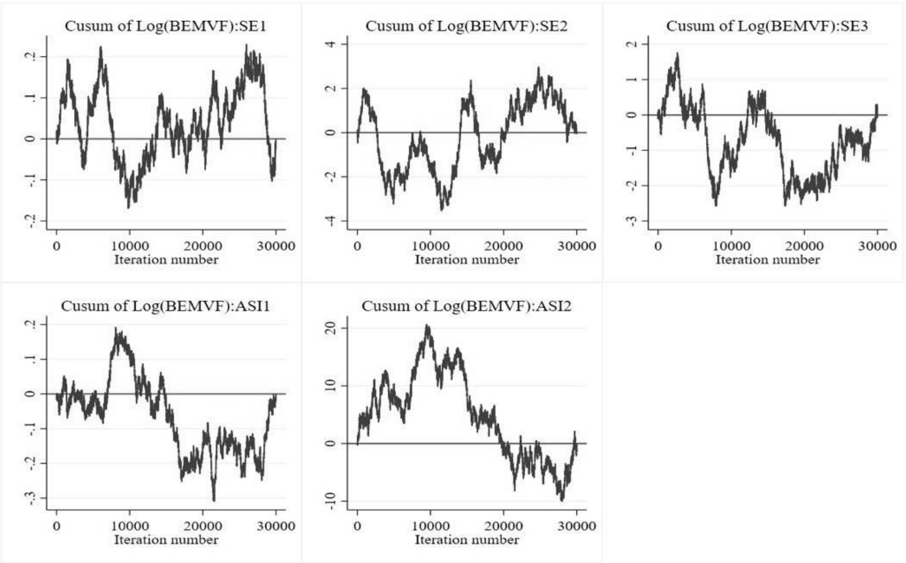
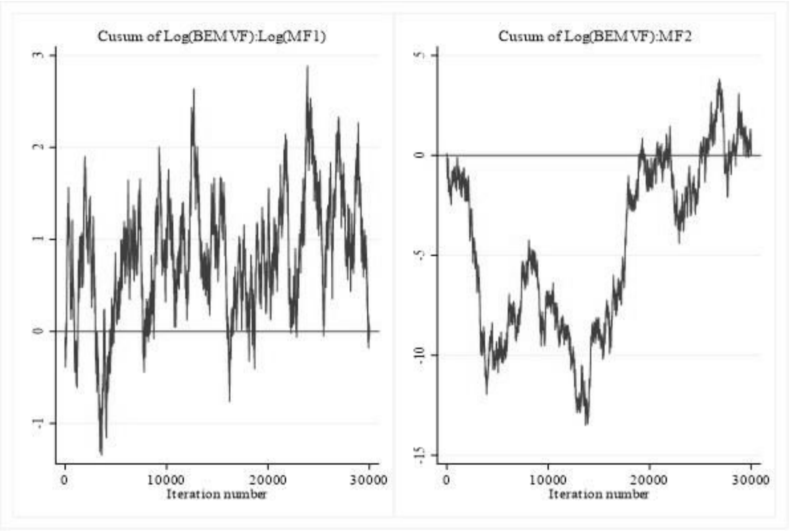
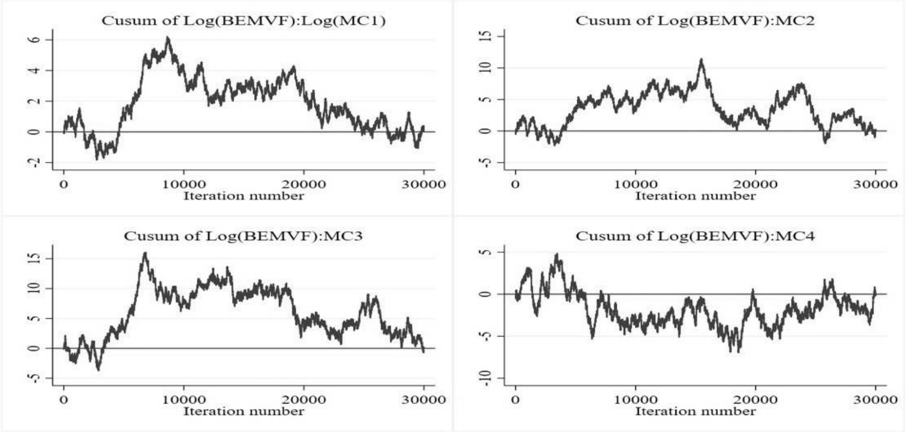


Figure 2. Cusum of market forces variables



3. Complementary, cumulative sum plots for marketing channel variables (Figure 3) illustrated that there are no convergence problems. However, in the case of {Log(BEMVF): Log(MC1)} and {Log(BEMVF): MC2}, after the first nearly 5,000 iterations, the cumulative sums (i.e., cusum) curve stays in the positive y plane and by the end it recovers and crosses the x-axis several times. In the case of {Log(BEMVF): MC4) after the first nearly 5,000 iterations, the curve stays more in the negative y plane but still crosses the x-axis numerous times.

Figure 3. Cusum of marketing channels variables



4. By examining cumulative sum plots for intercept term and sigma2 (Figure 4), no contrast between the jagged lines of the fast-mixing parameters can be observed. However, in the case of{sigma2}, the cumulative sums (i.e., cusum) curve stays in the negative y plane, after the first half of iterations and in the positive y plane, after the second half of iterations. Comprehensively, during all iterations, it seems that both parameters registered a well-mixing chain, and in an exceptional way intercept term.

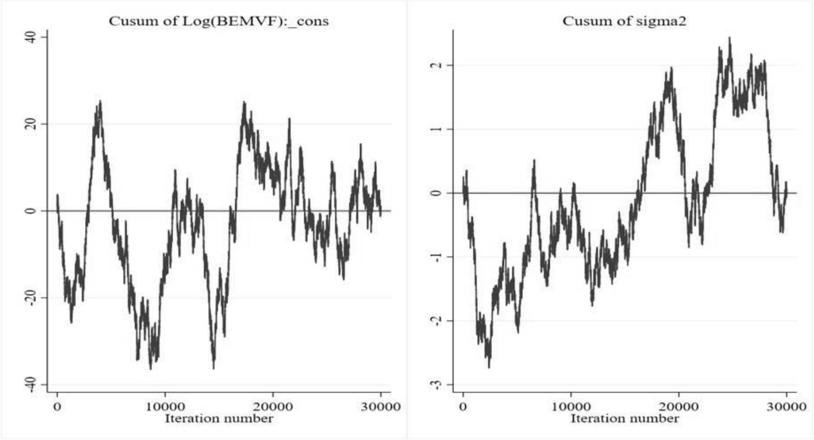


Figure 4. Cusum of constant and sigma2

Efficiency summaries

In our MCMC sample size, we have 30,000 independent observations to obtain estimates (i.e., ESS) for {Log (BEMVF): all predictors} and only about 28,827 independent observations to obtain estimates for {sigma2} (Table 5. Efficiency summaries).

Table 5. Efficiency summaries

Terms	ESS	Corr. time	Effcy.
Log (BEMVF)			
SE1	30,000	1.00	1.00
SE2	30,000	1.00	1.00
SE3	30,000	1.00	1.00
ASI1	30,000	1.00	1.00
ASI2	30,000	1.00	1.00
Log (MF1)	30,000	1.00	1.00
MF2	30,000	1.00	1.00
Log (MC1)	30,000	1.00	1.00

Terms	ESS	Corr. time	Effcy.
MC2	30,000	1.00	1.00
MC3	30,000	1.00	1.00
MC4	30,000	1.00	1.00
Intercept	30,000	1.00	1.00
sigma2	28,826.62	1.04	0.96

Source: *Authors' processing in STATA17*

In our example, the estimated lag (i.e., Corr. Time), after which autocorrelation in an MCMC sample remains small, is approximately 1 for all parameters.

Related to efficiency, it can be seen that are 100 % for independent variables, and about 96 % for sigma2, which are good for an MH-Gibbs sampling algorithm.

Bayesian information criteria and model tests

For selecting a model, a set of Bayesian information criteria is used to evaluate the models that are most likely to fit the data. Likelihood-based methods are recognized for overfitting the data, which can be caused by the addition of more parameters in a model (Ghasemian et al., 2019). This is why the use of a penalty is significant to diminish the likelihood of overfitting (i.e. Table 6. Bayesian model tests).

The three most common information criteria used for picking a model are the Akaike information criterion, Bayesian information criterion, and the deviance information criterion (i.e., DIC) (Evans, 2019). These criteria are likelihood-based, and they include a penalty term and a good-of-fit term. Models with smaller values are preferred.

Table 6. Bayesian model tests

Parameter	DIC	log (ML)	log (BF)	P(M)	P(M|y)
active	*801,302*	*-492,836*	*1.0000*	*1.0000*	*1.0000*

Source: *Authors' processing in STATA17*
Marginal likelihood (ML) is computed using Laplace–Metropolis approximation

The Bayes factors (i.e., BF) require that the distribution be completely specified. This is particularly important in MCMC simulations because BF include all information about the specified Bayesian model. In our case, the logarithm of the Bayes Factor (i.e. log (BF)) is 1, which suggests that there is minimal evidence against the model (Kass and Raftery, 1995). Computing posterior probabilities of the model (i.e., P(M|y), it is clear that the model has the highest probability of 1.00. When computing the posterior probabilities of the model (i.e. P(M|y)), it becomes evident that the model has the highest probability, which is 1.00.

Conclusions

This paper estimated the value market of Romanian small farms. Data were collected based on personal interviews with a sample of small farms distributed over the 5 historical geographical areas: Transylvania, Oltenia, Muntenia, Moldova, and Banat. The Gibbs sampling and updates of the Metropolis-Hastings algorithm were applied to investigate farmers' assessment of market value depending on the social and economic characteristics of the small farms.

Results asserted the a priori hypothesis, from the interpretation of (9) overall small farm attributes that those contribute positively and significantly to the estimated market value.

However, socio-economic factors influenced the elasticity of the dependent variable in different ways. Specifically:

1. *Farmer's Age:* The age of the farmer (farm owner) had a relatively low negative influence on the estimated market value of small farms. This is due to the sample predominantly consisting of younger farmers who own small farms (Ahearn et al. 1993).
2. *Education and Household Members:* Education levels (ranging from level 1 to 7) and the number of household members caused a moderately positive increase in the market value (Mishra et al. 2002).
3. *Direct Payments and Support Programs:* Direct payments had a slightly negative impact (Morkunas/Labukas 2020), while support for Agri-environmental activities and Less Favored Areas (LFA) had a positive influence. This suggests that the logarithm of the estimated market value of farms (Log(BEMVF)) is quite responsive to changes in these support measures (Brown et al. 2019).
4. *Marketing Factors:*

   Distance to Nearest City: The distance between the farm and the nearest city had a positive influence on the response variable (Migose et al. 2018).

   Sales Price Differences: Differences in sales prices across distribution channels also registered a positive influence, with this factor being the most significant among the regressors (Milford et al. 2021).

5. Sales Venues:

- Street Markets, Marketplaces, and Bazaars: Sales in these venues positively influenced the output variable (Mejia et al. 2022).

- Processing Plants: Sales to processing plants had a positive effect (Owoo/ Lambon-Quayefio 2017).
- Direct Sales: Direct sales from farms to neighbors and tourists by the roadside (Kinoshita 2001; Rajagopal 2012; Anisimova 2022) and sales at trade fairs also positively influenced the market value (Oumlil et al. 2015).

Overall, these socio-economic factors demonstrate varying degrees of impact on the elasticity of the market value of small farms.

Appendix 1

Model summary with OLS estimates

Parameters	Log (BEMVF)	[95 % Conf. Interval]	
SE1 Age	-.0035	-.0085	.0014
	(.0025)		
	[-1.40]		
SE2 Education	.0266	-.0319	.0857
	(.0299)		
	[0.89]		
SE3 Number of household members	.0716 **	.0242	.1191
	(.0241)		
	[2.97]		
ASI1 Direct payments	-.0078 ***	-.0121	-.0034
	(.0022)		
	[-3.54]		
ASI2 Support for Agri-environmental	.2055 *	-.0359	.4471
activities and LFA	(.1232)		
	[1.67]		
Log (MF1) Distance between farms	.0522	-.0156	.1198
and the nearest city	(.0352)		
	[1.48]		
MF2 Difference in sales prices for	.4526 ***	.3083	.5976
distribution channels	(.0739)		
	[6.12]		
Log (MC1) Sale on the street markets,	-.2369 ***	-.3096	-.1642
marketplace, bazaar	(.0376)		
	[-6.29]		
MC2 Sale to processing plants	.4046 ***	.2706	.5392
	(.0684)		
	[5.92]		

Parameters	Log (BEMVF)	[95 % Conf. Interval]	
MC3 Sale directly from the farm to neighbour's, tourists, by the roadside	.1236	-.0425	.2904
	(.0847)		
	[1.46]		
MC4 Sale at trade fairs	.3123 ***	.1673	.4569
	(.0735)		
	[4.25]		
Intercept	12,398 ***	11,679	13,112
	(.3689)		
	[33.6]		

Note: SE statistics in (), t statistics in [], * p <0.1, ** p <0.01, *** p <0.001
Source: *Authors' processing in STATA17*

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