Does policy support really help farmers' incomes:
the case of Kosovo

by Philip Kostov, Sophia Davidova, and Ekrem Gjokaj

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Abstract

This paper estimates the effect of public policy support - direct payments and investment subsidies - on agricultural incomes in Kosovo. The study employs a unique data collected in 2019 with the purpose to assess the impact of financial support on agents along the food chain. Five different unconditional quantile regressions for a range of different quantiles have been estimated. The paper compares the results from these estimations to a conventional mean regression. In order to obtain comparability, all quantile coefficients have been standardised. The results show significant heterogeneity in the effects of the covariates on agricultural incomes, suggesting that since the standard regression ignores it, it is likely to present misleading results. The results indicate that the mean regression grossly overestimated the effect of direct payments and to a lesser degree the effect of investment subsidies, particularly in the middle of the distribution. From policy point of view, the directs payments helped mostly the wealthiest farmers. However the greatest positive effects of investments subsidies is that for poorest farmers, who are also benefiting more from direct payments than the average farmer.

Key words: unconditional quantile regression, direct payments, investment subsidies, farm incomes, Kosovo.

JEL Codes: C14; C21; Q18

1. Introduction

This paper is motivated by the fact that, despite being one of the poorest countries in Europe, Kosovo dedicates a substantial budget to agricultural support. It is therefore important that taxpayers' money contribute effectively to the standard of living of farmers and to their farm incomes.

Farm incomes have been a major focus of agricultural support policies, directly or indirectly. There are several strands in the agricultural economics literature which, using different methodologies, investigate the effect of agricultural support on farm incomes emphasising different aspects, e.g. income risk (variability), transfer efficiency, income distributions (inequality),. The bulk of the studies have been concerned with the effect of reforms of the EU Common Agricultural Policy (CAP) or the US policy.

A large body of research focuses on the effect of public support on farm income risk (e.g. Poon and Weersink, 2011; Fertő and Stalgienė, 2016; Severini et al., 2016). Most of the studies have revealed a negative covariance effect, thus government payments reduce farm income volatility. Yet, some authors argue the opposite - since government payments do not involve risk they induce risk averse farmers to use risky inputs and, thus, ultimately increase income volatility (Serra et al., 2005).

The second strand analyses transfer efficiency, i.e. the extent to which farm support reaches the target beneficiaries – farmers or is leaking to other agents in the chain, i.e. land owners, or up- or downstream agents (e.g. Roberts et al., 2002; Patton et al., 2008; Guastella et al., 2013; Michalek et al., 2014; Ciaian et al., 2015). In general, the studies show that coupled subsidies leak more, in particular to land rents, than the decoupled payments. Additionally, the effect depends on the conditionality of payments and production characteristics of agricultural commodities.

The third body of research deals with the distributional consequences of agricultural policies (e.g. Allanson, 2006; Mishra et al., 2009; Moreddu, 2011; Severini and Tantari, 2013; Deppermann et al., 2014; Piet and Desjeux, 2021; Hanson, A., 2021). Most, but not all studies dealing with the effect of policy payments on income distribution, used the Gini coefficient. Mishra et al (2009) looked at the regional effect of US government programmes on incomes in agricultural regions and concluded that government programmes helped decrease income inequality in some regions. Alanson (2006) used the difference in the Gini coefficients pre- and post-support and concluded that agricultural support has been an inefficient redistributive instrument. Investigating the effect of CAP payments Piet and Desjeux (2021) argue that CAP payments help decrease income inequality, but Pillar 1 and 2 payments perform differently along the distribution. Obviously the results depend very much on the methodology used and the particular policy instruments. We, in this paper, also try to evaluate the effect of public policy support on agricultural incomes in Kosovo. Our data is specifically collected to assess the impact of financial support to farmers and, second, we adopt unconditional quantile regression framework in order to provide more complete characterisation of these distributional effects.

The results show that the lowest income farmers benefited from agricultural policy support, particularly from investment subsidies. Direct payments helped narrowing down the income gap between the poorest farmers and the medium of the distribution but the gap between the two tails – poorest and richest incomes has widened. From the methodological point of view, the results from the quantile regression have been compared to the linear mean regression. Due to the heterogenous effect of covariates in different quantiles of income distribution the standard (mean) regression provides misleading results.

The paper is structured as follows. The next section includes a brief overview of agriculture policy in Kosovo, and section three presents the data and the construction of variables. The fourth section presents the methodology and section five discusses the results. Section six concludes.

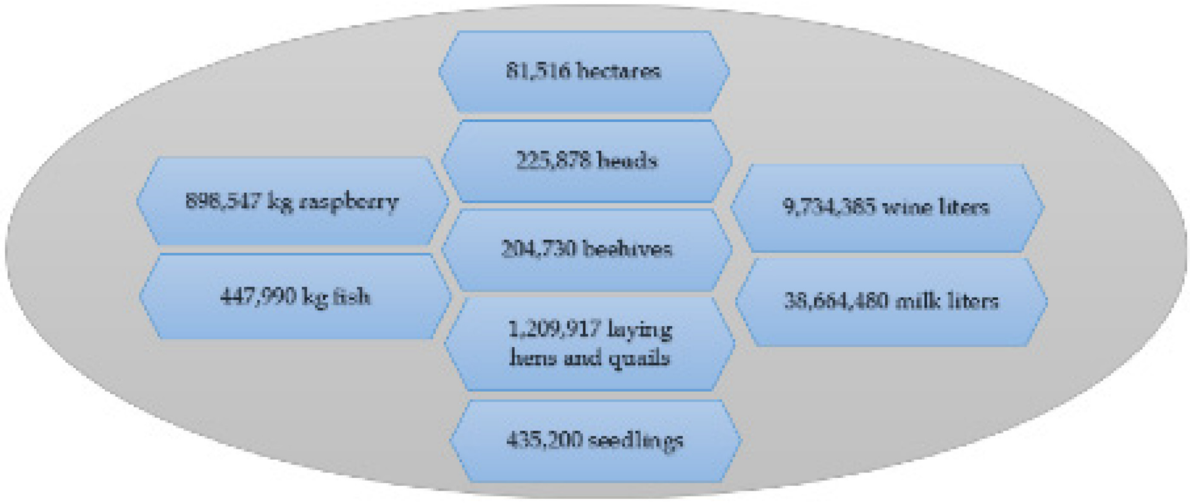
2. Brief overview of agriculture policy in Kosovo

Kosovo is one of the poorest countries in Europe. In 2018 the GDP per capita was only €3,746 (MAFRD, 2020). In line with the other countries in the Western Balkans, agriculture is an important sector in Kosovo, contributing to 7.2% of GDP in 2018 (DEAAS, 2021). Kosovo's agriculture is characterised by serious structural problems. These include land fragmentation, low labour efficiency and high production costs (MAFRD, 2018). The majority of farms are very small in physical size. According to the Agricultural Household Survey, carried out by the Kosovo Agency of Statistics, in 2019 there were 105,289 agricultural holdings (MAFRD, 2020). According to land area, the largest proportion – 69.7% were smaller than 2 ha, while only 1.5% were larger than 10 ha, the latter accounting for 18.3% of arable area.

Two programmes for support have been implemented, copying to a certain extent Pillar 1 and 2 of the EU Common Agricultural Policy – direct payments as per Pillar 1 and investment subsidies (grants) as per Pillar 2, rural development. The amounts allocated for the two programmes in 2018 were €29.6 and € 31.0 million respectively (DEAAS, 2021). Most of direct payments have not been decoupled yet. In view of the fact that the composition of direct payment support has a large share of payments for commodity output, OECD concluded that this form of support is ‘unlikely to facilitate long-term productivity gains and competitiveness’ (OECD, 2018, p. 549).

In more concrete terms, support through direct payments was disbursed for crops on the basis of hectares cultivated while for livestock, the payments were mainly per head. The chart below summarises the quantities/ numbers subsidised through direct payments.

Chart 1: Quantities/number of units subsidised through direct payments in 2019



Source: MAFRD (2020) Green Report, p. 181.

The total number of applicants for direct payments in 2018 was 50,054 of which 48,320 were successful and only 1,734 (3.5%) were rejected, mainly due to the lack of necessary documents. (MAFRD, 2020). Therefore, applicants can have reasonable expectations to be successful.

Kostov et al. (2021) analysed the effect of subsidies on farm commercialisation in Kosovo. They argue that since direct payment recipients have to meet some conditions, most often to be of a minimum size, mainly more commercial farms are beneficiaries of direct payments. Given the structure of Kosovo farms, it is expected that beneficiaries are biased towards larger farm sizes. If this is the case then direct payments would disproportionally benefit larger farms and hence exacerbate the income differential between poorer and better-off farmers. Such an outcome would however be undesirable where income support is an intended consequence of agricultural support measures. It is therefore imperative to investigate this particular issue. We are hence particularly interested whether public policy supports incomes of smaller (low income) farmers and whether it closes or exacerbates the gap in farm income distribution between poorer and richer farmers.

Investment subsidies (under the Rural Development programme) have been aimed to support investment not only in farming, but also in the processing industry, rural tourism, as well as irrigation. In 2018, 618 projects were supported (DEAAS, 2021). The projects were under the following rural development measures: investments in physical assets in agricultural holdings; investments in physical assets in processing and trading with agricultural products; diversification of farms and business development; irrigation of agricultural lands; implementation of local development strategies; special programme for socio economic integration of small farms, the only one exclusively focused on small farms.

3. Data and variables construction

The study uses data collected in the second half of 2019 through a survey organised by the Kosovo Ministry of Agriculture, Forestry and Rural Development (MAFRD). The objective of the survey was to assess the impact of financial support programmes provided by MAFRD and implemented by the Agency for Agricultural Development (ADA) on agents alongside the food chain. Concerning farming, in addition to the impact of financial support through direct payments and investment subsidies, the Ministry aimed to collect information on various other aspects of farm activity, e.g. the structure of farms, crops and livestock production, input expenditure, sales channels etc. The data referred to 2018.

The survey included several panels in respect of pre-determined agents along the food chain – farmers, food processors, traders and consumers. For this paper, we employ the data from the farmers panel. The farmers questionnaire was the longest and the most detailed (291 questions). Understandably, the survey length has negatively affected the data quality and in some variables there were many missing observations. Another data limitation is that data on output and prices was not collected. However, what was useful for the analysis in the paper was the data on farm and off-farm incomes, and detailed information on various support instruments and the policy beneficiaries. For many variables the survey collected information not only for 2018 but also for the past 5 and 10 years. The latter allowed us to define some support variables.

The interviews were conducted by enumerators in-person. For the sample, initially the list of all farmers registered with the Agricultural Development Agency was consulted. Out of this list, 1,000 beneficiaries of agricultural policy support and 200 non-beneficiaries were selected randomly. Geographically, the survey covered all 6 regions in the country with the highest number of respondents in the region where the capital Pristina is located - 327 or 26.1 per cent.

Preliminary inspection of the data led to removal of observations where we had missing values in the variables of interest. As a result, the sample used in the analysis includes 540 observations.

Table 1 presents summary statistics for the employed variables. The investments measure reflects investments carried out over the last 10 years. Although the survey asked for the specific year of every piece of investment, we do not disaggregate these by year in order to avoid fragmenting the investments by lag. If we were to do so, due to the small number of observations (out of 540 farms only 323 had made any investments over the last 10 years), this would result in small support in terms of number of observations for each such lagged investment effect. In aggregating the investment we estimate an aggregated effect the strength of which will depend on the term structure of these investment and the actual lag needed for this effect to materialise. Nevertheless, using what is essentially an investments stock variable, we were able to better capture the investment effect since the latter relies on investment made in previous years. The investments subsidies have been measured in exactly the same way. For every investment, where applicable, the relevant amount of investment subsidies was recorded. Therefore, the investment subsidies measure also takes a longer term outlook. The DP (direct payments) variable captures the coupled payments received in 2018. For completeness we added to it the other ad-hoc subsidies obtained by farmers. In the sample, only 25 farms obtained such additional support, normally coming from the municipality in addition to what they received from the Ministry budget, and the amounts received were relatively small. The major difference between DP and investment subsidies is that the DP are essentially a flow variable added to current year cashflows of the operators. However, given the stable nature of the DP support mechanism in Kosovo, and the fact that the procedure to apply for direct payments has been straightforward and the applicants did not face significant barriers, we assumed that they would closely follow the dynamics of previous year direct payments and therefore their value could also be used as a proxy to measure the potential effect of the DP regime in general. Age is the age of the farm owner (head of the household), gender is an indicator variable with values of 1 indicating males and 0 females. Education is an ordinal variable with natural hierarchy measured by a 5 point scale with higher values indicating higher levels of educations. Since it would not be reasonable to expect that moving between two adjacent education categories would always have the same effect, it would have been more realistic to express education as a set of indicators. However, in this study the main analytical focus is on the effect of public support and for this reason we use a single ordinal education variable as a very rough indicator. Contract coverage measures the extent to which farmers' contracts with buyers cover different conditions and contingencies. For farmers who did not have any buyers contracts this variable takes a zero value, while for farmers which have such contracts irrespective of their nature (written, verbal or other) this variable counts how many of the 15 pre-specified attributes in the questionnaire are included in the contract. These attributes are: quantity to be purchased, minimum purchased quantity, fixed price, price range (minimum and maximum price), variable price based on quality (premium quality), frequency of delivery, minimum quality, requirements for the type and amount of inputs (e.g. pesticides), feed or veterinary procedures / sanitation, obligation to purchase inputs from the buyer, packaging requirements, payment time, penalties for termination of the contract, services to be provided by the buyer, problem solving mechanisms and duration (lifespan) of the contract. The more of these attributes are present in the contracting agreement, the better defined the marketing outcomes will be and therefore it is expected that this will reduce the marketing risks for the farmers and hence increase their incomes. The buyer non-compliance variable counts how many of the same 15 attributes have been violated by the buyers. It is, therefore, expected that such non-compliance will act in the opposite direction to contract coverage and increase the risks for the farmers. Finally, the ease to change a buyer is a 5-point scale evaluation by the farmers which proxies an aspect of their market access opportunities. Greater such ease, and hence better market opportunities, is expected to benefit farm growth and farming incomes.

Table 1. Summary statistics

	Mean	Standard deviation	Min	Max
Agricultural Income (€)	9,586	19,939	120	234,000
Non-agricultural Income (€)	8,867	37,921	90	576,228
Investments(€)	37,925	87,835	0	957,000
Investment Subsidies(€)	13,647	36,020	0	434,000
DP (€)	1,478	3,283	0	54,000
Age (years)	48	14	20	85
Gender (male=1)	0.89	0.32	0	1
Education (1-5)	3	1	2	5
Contract coverage (count)	5	4	0	15
Buyer noncompliance (count)	2	3	0	15
Ease to change buyer (1-5)	3	1	1	5

4. **Methodology**

The methodology includes estimations with linear (mean) regression and with unconditional quantile regression. The logic behind this strategy is, first, to see whether on average there is a positive impact of agricultural support payments on farmers' incomes, and second, to look at an issue of even greater interest - who benefits most – are those the larger farmers, or the smaller ones who are in greater need of support, in other words is Kosovo agricultural policy regressive or progressive. Such questions are in general central in investigating the policy effects on incomes but they are even more important in a country like Kosovo where most farms are quite small generating meagre incomes.

The unconditional quantile regression, commonly referred to as re-centered influence function (RIF) regression (although the latter term is much more general) follows Firpo *et al* (2009). In essence it consists of estimating the RIF of the quantiles which is $q_\tau + (\tau - 1(Y \le q_\tau))/f_Y(q_\tau)$ where $1(.)$ is the indicator function, $f_Y(.)$ is the density function of the dependent variable Y and q_τ is its unconditional τ-quantile. As long as the density function is given (and it can be estimated by standard kernel methods), the above quantity is simple to calculate. Then it can be regressed on a set of covariates in order to obtain the unconditional partial effects of the covariates, which in the case of linear specification are simply the estimated linear coefficients.

It would be useful to contrast the unconditional quantile regression to the much more widely used conditional quantile regression. Indeed when the empirical literature mentions the term quantile regression it almost exclusively refers to the conditional quantile regression model. Although it is possible to relate the conditional and unconditional quantiles to each other in the sense that every unconditional quantile can be represented as a weighted average of conditional quantiles, such relationships are far from trivial and will not be discussed here. Instead, we will focus on the interpretation of the coefficients derived from such models. The conventional conditional quantile model investigates the effects of covariates on the conditional distribution of the covariates. The main shortcoming of this model is that it is not always easy to interpret, and although there cases where it is useful (see e.g. Kostov *et al.* 2018), in many other cases this is far from straightforward. If we take, for example, the present study, the upper conditional quantiles would refer to farms which given their characteristics (i.e. the covariates included in the model) are able to extract more income that other comparable farms. This is, however, also conditioned on both the covariates (i.e. model specification) and the actual estimation sample. Changing or modifying any of the above will change the interpretation. The unconditional quantile regression model, chosen in this paper, in contrast, analyses the unconditional quantile of the outcome variable. Unlike conditional quantiles which depend on model specification and are therefore not observable. the unconditional quantiles are directly observable and can be easily interpreted. Modifying the model specification also is not a considerable problem, since it does not change the outcome. The unconditional quantile regression provides directly the effect of the covariates on the unconditional quantile of interest. In principle, the sample used to estimate such effects does not need to be representative of the overall population, since results may be generalised using the values of the outcome variable at these quantiles.

Furthermore, in this paper we compare these results to a conventional mean regression. Linear (mean) regressions are the workhorse of empirical economics and such comparison would be useful in deducing the potential issues with the mainstream approach to analysing the effects of agricultural subsidies. To this end, it is important to reinterpret the mean regression with regard to its quantile counterparts. In order to achieve this, we assume for simplicity and in accordance to the empirical approach adopted in the study a linear functional specification for both mean and quantile models. While quantile regression models estimate each quantile separately and hence allow for different effect across the distribution of the dependent variable, the mean regression assumes that these effects do not change along the distribution of the outcome variable. So the first difference is that unlike a linear mean regression, the linear quantile regression is essentially a non-linear model in which every quantile has a different (linear specification) and when these different specifications are aggregated the result will be a non-linear relationship between the dependent and independent variables. The mean regression is in a way an approximation to the more general non-linear quantile model, which averages the corresponding effects. If the above were the only differences, then the disadvantages of the mean regression would not be so serious, since it estimates the average partial effects, of say direct payments on income, as opposed to the unconditional quantile partial effects. It is, of course, more informative and useful to obtain the quantile effects, but in some cases the average policy effects could be all the policy community is interested in.

However, there are disadvantages of the mean regression from the point of view of heteroscedasticity. The set of different quantile models typically have different variances, since they are not constrained or related to each other in any meaningful way. Looking at this from the point of view of the mean regression means the presence of heteroscedasticity. One could then hope that estimating some robust (to heteroscedasticity) estimates would solve the problem. Unfortunately, this is not the case. Such estimates assume (and model) heteroscedasticity as systematic function of the variables used in the model. The set of quantile regressions however does not assume any such systematic variation and is, therefore, much more general and less restrictive. Furthermore by design such 'robust' estimates do not change the point estimates. If we were to aggregate the quantile partial effects (i.e. coefficients), however, the variances would affect the average estimates. In essence, the problem of obtaining an average partial effect from a set of quantile partial effects is similar to estimating a mean from several samples and can be obtained as a weighted average of the quantile partial effects with weights proportional to the inverse of their associated variances. This means that the average partial effects that can be derived from quantile models depend on their variances and, due to this, cannot be directly compared to a mean regression, where the presence (or absence) of heteroscedasticity does not affect such effects at all. This means that when the variances of the quantile models at different quantiles are quite different, the mean model estimate for the average partial effect may be biased. And even if this is not the case, since the mean model can be thought of as averaging different quantile variances, inference based on such averages may be misleading in terms of inferred statistical significance. The above points are referred again when considering the empirical results.

5. Discussion of results

Five different quantile regressions for a range of different quantiles have been estimated. The aim was to provide a reliable coverage of agricultural income distribution by using a relatively small number of quantiles to allow for a tabular representation of results. For this purpose, we used the quartiles of the distribution and complemented them by two tail quantiles - the 0.1^{th} and the 0.9^{th}. The consideration not to go deeper into the tails (e.g. looking at the 0.05^{th} and the 0.95^{th} quantiles) has been to avoid analysing less typical in terms of farming income quantiles.

The results from the estimations are presented in Table 2, alongside the results from a conventional mean regression. In order to make these results comparable we have made some simplifications. First, we have adopted the OLS approach to the RIF regression estimator. This is, however, more innocuous that it appears, since the alternative estimation methods suggested in Firpo *et al*. (2009) produce very similar results. For inferential purposes, we have used 500 bootstraps (see Efron and Tibshirani, 1986) to derive approximate P-values for the estimates. We have used region-clustered standard errors for both the unconditional quantile regressions and the mean model although not using clustered standard errors does not qualitatively change the results.

To facilitate the interpretation, the actual values of agricultural income at these quantiles, as well as the mean agricultural income (in the mean regression column) are also presented. The first point to underline is that there appears to be a considerable variation of the effects across the different quantiles, suggesting significant heterogeneity in the effects of the covariates on agricultural incomes. This suggests that since standard regression ignores such heterogeneity, it is likely to present misleading results. Then we can look at the statistical significance of the effects for different quantiles. The effects are significant across most quantiles. There are a couple of exceptions, namely the effect of education in both tails, the effect of investments for low income farms and investment subsidies for the high income farms, which are statistically insignificant, but overall the model explains agricultural income across its distribution. Contrast this to the mean model where the three background variables (age, gender, education) and the contract coverage are all insignificant. Qualitatively then the mean model would be unsatisfactory. The latter results illustrate the point we have made in the previous section that even if the mean model provides consistent averaging (which we do not know for sure yet) it can provide erroneous inference due to the implicit bias in the estimated standard errors.

Let us now review the estimated effects. Non-agricultural income increases agricultural income. Such an effect is to be expected for at least two reasons. First, non-agricultural incomes can be used either directly or indirectly (in that they facilitate loan approvals) for investment purposes. Second, higher incomes can create a wealth effect and reduce risk aversion, hence leading to a higher degree of innovative entrepreneurial behaviour which should benefit agricultural incomes. Investments, as expected, increase agricultural incomes, although there does not appear to be a discernible effect at the lower tail. Taking into account that the 0.1th quantile farm income is only 800 euros, it is likely that such an entity would not implement purely commercial logic. Direct payments have an income enhancing effect. Age is found to reduce income, even though the average age in our sample is quite low - 48 (see Table 1). The gender effects, although formally significant, appears to be highly unstable and switches signs over the different quantiles. Given that the reference group (female) only accounts for 11% of the observations, it becomes difficult to estimate reliably such effects for specific quantiles and hence the results need to be taken with some caution. More comprehensive contracting (in terms of higher contract coverage) and better marketing opportunities (i.e. the ease with which buyers can be replaced) increase agricultural incomes, while the buyers non-compliance with the contract terms reduces the income.

It might be tempting to compare the different coefficients for the same covariate in Table 2. This is often used when conditional quantile regressions are employed. However, such direct comparison would be misleading. To explain this, let's consider the 0.1th quantile and the median, the 0.5th one. Since we directly observe their sample income values and these are correspondingly €800 and €4000, we know that, in this instance, the median income is 5 times greater than the one in the tail (0.1th quantile) farm. Hence, the estimated coefficients show the effect of the covariates for two very different levels of income, one of which is considerably higher than the other. In this case, in order to be comparable to the median effect, any effect in this lower tail will need to be multiplied by 5, so that these two effects become comparable in relative terms. In a more general vein, all unconditional quantile regression coefficients need to be transformed in similar relative terms to be made comparable. Since we would also like to include the mean regression in such comparison, we suggest to standardise by multiplying the coefficients at each quantile τ by μ/q_τ, where μ and q_τ are correspondingly the mean and the unconditional τ - quantile of the dependent variables (agricultural income). The inverse values of these ratios (the ratio to mean income, which is q_τ/μ) are presented in the upper part of Table 2, next to the values of q_τ.Then if we divide all quantile coefficients by these ratios we will obtain comparable effects across quantiles, which could also be compared to the mean regression coefficients. These 'standardised' coefficients are presented in Table 3 which can be used to directly compare these effects across the quantiles and to the mean regression.

Note, furthermore, that due to the highly skewed and leptokurtotic nature of the agricultural incomes distribution, the mean should not be compared to the median. In fact, out of the five quantiles considered in this paper it is the third quartile where the agricultural income is closest to the mean agricultural income. Therefore, in this particular case the third quartile results should be the closest equivalent to the mean results. This on its own raises questions about the possible applicability of mean regressions to investigate effects of covariates on agricultural income. In this particular case, even if the multitude of possible technical issues related to the comparability of mean regression discussed in the methodology section did not arise, one may say that it should be similar to a regression of a third quartile of the agricultural incomes farm, which means that the mean regression will be implicitly biased towards larger farms, while most of the farms in the sample (and in Kosovo in general) are much smaller. Therefore, any such results would by definition be unrepresentative of Kosovo agriculture.

Table 2. Estimation results

	Mean regression		0.1th quantile		0.25th quantile		0.5th quantile		0.75th quantile		0.9th quantile	
	Agricultural Income	Ratio to mean income	Agricultural Income	Ratio to mean income	Agricultural Income	Ratio to mean income	Agricultural Income	Ratio to mean income	Agricultural Income	Ratio to mean income	Agricultural Income	Ratio to mean income
	9586	1.00	800	0.08	1500	0.16	4000	0.42	10000	1.04	20000	2.09
	Coefficient	P Value	Coefficient	P Value	Coefficient	P Value	Coefficient	P Value	Coefficient	P Value	Coefficient	P Value
Intercept	4348	0.46	1333.6	0.00	3580.11	0.00	8112.03	0.00	5692.91	0.00	16095.56	0.01
Non-agricultural Income	0.0733	0.00	0.0034	0.00	0.0059	0.00	0.0142	0.00	0.0344	0.00	0.1705	0.04
Investments	0.0424	0.00	-0.0009	0.46	0.0015	0.00	0.0073	0.00	0.0167	0.00	0.1202	0.00
Investment Subsidies	0.0671	0.05	0.0068	0.02	0.0064	0.02	0.0159	0.00	0.0456	0.00	-0.0688	0.19
DP	2.2440	0.00	0.0653	0.00	0.0963	0.00	0.1384	0.00	0.6554	0.00	3.7328	0.01
Age	-64.7500	0.24	-24.4683	0.00	-23.5128	0.00	-54.7975	0.00	-147.8439	0.00	-239.4498	0.03
Gender	506.5000	0.83	355.4638	0.00	-419.3589	0.00	-1369.0975	0.00	529.9393	0.48	-9845.1204	0.02
Education	-1329.0000	0.23	-23.0884	0.72	-454.8160	0.00	-918.8298	0.00	-219.2078	0.09	402.3503	0.73
Contract coverage	116.9000	0.54	16.1682	0.06	37.2901	0.00	59.2868	0.00	109.0672	0.00	862.5450	0.00
Buyer noncompliance	-506.0000	0.03	-121.0463	0.00	-91.3480	0.01	-242.7347	0.00	-416.7148	0.00	-1311.9843	0.01
Ease to change buyer	1768.0000	0.01	113.9904	0.02	279.1203	0.00	684.1134	0.00	2969.2915	0.00	3893.8593	0.00

Table 3. Standardised estimation results

	Mean regression		0.1th quantile		0.25th quantile		0.5th quantile		0.75th quantile		0.9th quantile	
	Coefficient	P Value	Coefficient	P Value	Coefficient	P Value	Coefficient	P Value	Coefficient	P Value	Coefficient	P Value
Non-agricultural Income	0.0733	0.00	0.0411	0.00	0.0374	0.00	0.0341	0.00	0.0330	0.00	0.0817	0.04
Investments	0.0424	0.00	-0.0106	0.46	0.0093	0.00	0.0175	0.00	0.0160	0.00	0.0576	0.00
Investment Subsidies	0.0671	0.05	0.0809	0.02	0.0408	0.02	0.0382	0.00	0.0437	0.00	-0.0330	0.19
DP	2.2440	0.00	0.7819	0.00	0.6156	0.00	0.3318	0.00	0.6282	0.00	1.7890	0.01
Age	-64.7500	0.24	-293.1774	0.00	-150.2552	0.00	-131.3160	0.00	-141.7165	0.00	-114.7629	0.03
Gender	506.5000	0.83	4259.1439	0.00	-2679.8563	0.00	-3280.8874	0.00	507.9759	0.48	-4718.5437	0.02
Education	-1329.0000	0.23	-276.6436	0.72	-2906.4402	0.00	-2201.8717	0.00	-210.1227	0.09	192.8374	0.73
Contract coverage	116.9000	0.54	193.7259	0.06	238.2977	0.00	142.0741	0.00	104.5469	0.00	413.3983	0.00
Buyer noncompliance	-506.0000	0.03	-1450.3695	0.00	-583.7470	0.01	-581.6862	0.00	-399.4440	0.00	-628.8044	0.01
Ease to change buyer	1768.0000	0.01	1365.8258	0.02	1783.6808	0.00	1639.4005	0.00	2846.2286	0.00	1866.2388	0.00

We should, of course, also take into account the well-known fact that the mean regression carries an explicit assumption that the estimated effects do not change along the distribution of agricultural income. Let us consider the effect of non-agricultural income in Table 3. In relative terms, it is similar across the first four of the employed quantiles, but it is about half or less of what the estimated mean effect is. The effect is indeed stronger in the upper tail (at the 0.9^{th} quantiles) but this difference cannot fully account for the estimated mean effect. It can, therefore, be concluded that the mean regression over-estimates the role of non-agricultural income and in doing so it weighs more heavily larger farms. Technically, this overestimation results from the differences in the variance at different quantiles that is not accounted for in the mean estimator. If we were to compute an average partial effect from these quantile effects, the larger estimates (at the 0.9^{th} quantile) will be weighted by the inverse of its variance. Since in this case the standard error of the non-agricultural income coefficient at the 0.9^{th} quantile is approximately 0.9 as opposed to 0.2 for the median, it should be weighted less in calculating an average effect. In fact, if we were to estimate the average partial effect of non-agricultural income from these 5 quantile effects we will get 0.03855461 as opposed to the mean regression estimate of 0.0733. In essence this is an example of outlier type of effect on estimated coefficients due to the assumption that all effects are the same in OLS regression. It is worth noting that at the third quartile (0.75^{th} quantile) where we can find a farm similar to the mean one, this effect is still half of what the mean model suggests.

The same qualitative picture emerges with regard to the effect of investments (as long as we ignore the 0.1^{th} quantile where the effect is insignificant). Investment subsidies exercise strongest income effects at the lower tail (the 0.1^{th} quantile), and these effects are not significant at the upper tail. These results suggest that investment subsidies reduce farming income inequality.

The effect of direct payments is slightly larger in the lower tail and significantly greater in the upper tail. Nevertheless, it is clear that the mean effect grossly overestimates this effect. The greater effect in the lower tail means that the poorer farmers do indeed benefit more in relative terms that the typical farms. However this effect is much stronger for the richest farms. Therefore direct payments have a two-fold effect. On one hand they exacerbate income inequality by disproportionally favouring the wealthiest farms. On the other hand however, it does compress the lower part of the income distribution towards the middle. Hence although the wealthiest farms are the main beneficiary from these payments, the poorest ones are, although to a smaller extent, also benefiting.

The age effect is most constraining for low income farms and while it is similar for the rest to the mean regression in this case underestimates it. Education has a negative effect (but not in the tails). This may on one hand appear counter-intuitive, but take into account that the ordinal measure of education used in this paper is, as discussed earlier, a rather imperfect measure. Presumably some measure of agricultural (rather than general) education would have been more appropriate.

Contract coverage is most important at the upper tail (highest income farms), followed by farms in the lower quartile, with weaker relative effects in the middle of the distribution. What is also noteworthy is that the mean model grossly underestimates its importance.

Buyer non-compliance is most damaging to the lower income farms. As for the ease to change buyer, it is least influential for the lowest income farms, with the other farms broadly at par, with exception to the third quartile where it peaks.

6. Conclusions

This paper is motivated by the fact that, despite being one of the poorest countries in Europe, Kosovo dedicates a substantial budget to agricultural support. The paper aims to investigate how this support affects farms in different quantiles of the agricultural income distribution and whether it helps closing the income gap. The study compares the results of unconditional quantile regression to those of a standard linear (mean) regression. In order to be able to compare the results in relative terms across different quantiles and with the ones from the mean regression the estimation coefficients have been standardised by multiplying each coefficient by the ratio of actual value of agricultural income at the respective quantile to the mean agricultural income for the sample. The results have led to several conclusions:

First, there is a considerable variation of the effects across the different quantiles, revealing significant heterogeneity in the effects of the covariates on agricultural incomes. This indicates that since standard regression ignores such heterogeneity it is likely to lead to misleading results. In fact, the results show that the mean regression grossly overestimated the effect of direct payments on farm incomes and to a lesser extent the effect of investment subsides (in the middle part of the distribution).

Second, overall the model explains agricultural income across its distribution. The effects of covariates used are significant across most quantiles. There are a few exceptions, namely the effect of education in both tails, the effect of investment for low income farms and investment subsidies for the high income farms, which are statistically insignificant.

Third, the study emphasises the importance of farmers contracts with downstream buyers for farm incomes and, in particular, the role of the content of the contract and the marketing opportunities. More comprehensive contracts in terms of the number of items determining the terms of the contract and better marketing opportunities, proxied by the ease with which farmers can replace the buyers, increase agricultural incomes, whilst the buyers non-compliance with the contract conditions reduces the income.

Fourth, the 'standardised' coefficients used to compare the effects of covariates across quantiles help reveal the effect of policy support on poorest farmers. Investment subsidies have the highest impact on poorest farmers (the lower tail). Direct payments have the strongest effect on the richest ones but the poorest come second with a larger effect than in the middle of the distribution.

Fifth, looking at the contracting, although the picture is not a clear-cut it appears that richer farmers benefit more from the better coverage of a contract and the marketing opportunities. It is not surprising since the poorest farmers are often semi-subsistence without opportunities to have a contract at all not let alone a contract with substantive coverage. Having said that, still the coefficients of contract coverage and the easiness to change the buyer are statistically significant and positive for the poorest farmers. The lowest income tail is the most damaged by the buyers non-compliance with the contract terms.

Overall, it seems that Kosovo agricultural support has tended to be closing to an extent the gap between the poorest farmers and farmers in the middle of distribution in terms of farm income, but at the same time it has increases the difference between the richest farmers and the middle of the income distribution. So we observe both positive and negative effects with regard to reducing income disparities. Therefore, although agricultural support is, in general, beneficial to the poorest farmers, it is not reducing income disparities. This means that more policy emphasis is necessary to support poor farmers to decrease the transaction costs to obtain comprehensive contracts with buyers and introduce real penalties for non-compliance which may decrease the income risk and enhance farm incomes of the poorest ones.

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