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Migration and farm technical efficiency: evidence from Kosovo

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Abstract

This article investigates the effect of migration on farm technical efficiency drawing on a large and representative sample of agricultural households in Kosovo. A two-stage estimation procedure is applied: a frontier technique to estimate the effect of migration on farm efficiency, followed by a propensity score based matching approach to robustly estimate the sample average effect on efficiency for different levels of migration intensity. Migration is found to have an efficiency decreasing effect, which is amplified for better educated workers. The observed negative effect of migration on efficiency is evident even at low levels of migration intensity.

JEL classifications: J61, J43, Q12

Keywords: Migration; Technical efficiency; Agricultural households; Western Balkans; Kosovo

1. Introduction

Rural areas in many developing and transitional economies have witnessed significant outmigration in recent years. Outmigration has tended to be relatively greatest from the most impoverished regions, which also are typically those most reliant on agriculture as a source of income and employment (Bolganschi, 2011). The impact on rural areas can be considerable, for instance studies for Bulgaria (Dittrich and Jeleva, 2009), Romania (Surd, 2010), and Ukraine (Peacock, 2012) describe villages either almost entirely depopulated or consisting of elderly residents and their grandchildren after those of working age migrated in search of better paid employment. This leads to an important question: what has been the impact of migration on agricultural efficiency?

This article analyses the impact of migration on farm technical efficiency in Kosovo, drawing on a large and representative survey of agricultural households. Technical efficiency of a given farm household refers to the "ratio of its mean production (conditional on its levels of factor inputs and farm effects) to the corresponding mean production if the farm utilized its levels of inputs most efficiently" (Battese and Coelli, 1992, p. 191). Kosovo was selected as a typical case where outmigration has been particularly high (Gashi and Haxhikadrija, 2012) and the majority of rural households engage in farming (ASK, 2012a).

The article focuses on the measurement of the effect of migration on technical efficiency as a primary objective for agriculture in Kosovo is to improve the efficiency of production, in preparation for desired accession to the EU. This is enshrined within Kosovo's Rural Development Plan, which states as an objective to improve "competitiveness and efficiency of primary agricultural production" (ARCOTRASS, 2006). While measuring technical change, as an essential component of growth in total factor productivity, would yield insights into the sources and level of dynamism in the agricultural sector, this requires comprehensive panel data which are currently unavailable. Hence, we focus on the quantitative assessment of the impact of migration on technical efficiency. The relationship between migration and technical efficiency is investigated under the following propositions: (i) product and factor markets in Kosovo are imperfect and (ii) a 'lost labor' effect is possible. The latter refers to the impact of migration on the production and income activities of those left behind (Pfeiffer and Taylor, 2007).

The impact of migration on farm efficiency is assessed using a two-stage estimation procedure: a frontier technique to estimate the effect of migration on farm technical efficiency, followed by a matching estimation approach to robustly estimate the sample average effect on efficiency for different levels of migration intensity. This two-stage approach accounts for empirical identification problems and lagged decisions.

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The article provides a more robust and nuanced analysis of the impact of migration on agricultural efficiency than present in some previous studies by considering the percentage of total available work time per household per year accounted for by migration (defined here as migration intensity).

The study contributes to the development literature, particularly the question of whether migration affects technical efficiency and if there is a relationship whether it is positive or negative. As Taylor et al. (2003, p. 79) note, although there has been much research on the contribution of migrants to host economies, the literature, however, "has neglected other important aspects of migration, such as the effects of migration on source communities." More recently, Taylor and Lopez-Feldman (2010, p. 83) argue that the "analysis of migration impacts is complex and challenging" and that "further econometric investigation is warranted." Although Kosovo can be considered an extreme case, most of rural Central and Eastern Europe has witnessed significant outmigration in recent years (OECD, 2012). Assessing the impact of migration on farm technical efficiency is thus of wider importance.

2. Theoretical considerations and previous empirical findings

In recent decades, various models of migration have been proposed and empirically tested (Massey et al., 1993). In neoclassical theory, individuals decide to migrate based on a comparison of expected costs and benefits. More recently, the New Economics of Labor Migration (NELM) relates migration to production and incomes in the households (communities) from where migrants originate (Stark and Bloom, 1985). It challenges the neoclassical assumption of individual decision making, arguing instead for a household perspective on the spatial allocation of labor. The NELM also acknowledges that migration typically occurs under conditions of market failure.

There are a number of potential reasons why migration may affect the technical efficiency of farms, bearing in mind that technical inefficiency is a measure of management error (Wouterse, 2010) and lower inefficiency does not correspond *per se* to higher yields or incomes. First, in the case of missing or imperfect credit and insurance markets, migrants can act as financial intermediaries who, through remittances, enable agricultural households, particularly those poor in liquid assets, to overcome credit and risk constraints (Taylor and Wyatt, 1996; Rozelle, et al., 1999). However, second, the impact of remittances on farm efficiency may be negative where they provide rural household members with an income that weakens the quality and intensity of their work. There is some evidence of this for Mali, where Azam and Gubert (2006) found that remittances provided incentives to shirk and reduce the intensity of work as households expect migrants to compensate any consumption shortfall. Gubert (2002) notes that migration creates a potential moral hazard—the effort of those who remain on the farm cannot be directly observed by migrants so that the latter cannot ascertain whether, for instance, low yields derive from shirking or noncontrollable climatic factors. Third, Mochebelele and Winter-Nelson (2000) argue that migrant households may find it more difficult to respond to intra-annual changes in farm conditions. This recognizes that farmers cannot perfectly forecast weather and thus also perfectly forecast how much and when labor input is required. Households with migrants may find it more difficult to mobilize labor rapidly and they employ it less effectively, so that they are less efficient than those who can employ the same input levels according to more flexible scheduling (Mochebelele and Winter-Nelson, 2000). Finally, a detrimental effect may be observed in the absence of perfect substitutes for lost household labor (Arslan and Taylor, 2012; Atamanov and Van den Berg, 2012). For example, family members may be more committed than hired farm labor (Zaiceva and Zimmermann, 2008) because they are directly interested in the final results of the farming operation as they are residual claimants (Allen and Lueck, 1998). Thus, family labor is better incentivized (Wilson and Jadlow, 1982), requires less monitoring of work effort and therefore is difficult to replace.

The theory relating to the relationship between migration and farm technical efficiency is, thus, ambivalent and empirical evidence is also conflicting (Table 1). For instance, Mochebelele and Winter-Nelson (2000) found that technical inefficiency was greater among nonmigrant households in Lesotho, suggesting that migrant households benefited from cash resources that allowed them to buy inputs when required and improve overall farm management. Similarly, Nonthakot and Villano (2009) in their study of efficiency of maize farms in Northern Thailand estimated that the duration of migration positively impacted on technical efficiency. However, in their analysis the number of migrants had no significant impact on technical efficiency. Rozelle et al. (1999), considering the impact of migration on maize yields and income, found that that the net impact of migration was negative although, in the case of income, remittances partially offset the loss. Jokisch (2002), while not formally testing the impact of migration on technical efficiency, argues that outmigration in Ecuador had little impact on farm production and land use.

One reason for the inconsistency in findings may stem from the treatment of migration. For example, as detailed in Table 1, much analysis has depended on a binary variable (nonmigrant vs. migrant households) that fails to capture what can be termed migration intensity: the percentage of household members absent and for how long. Nonthakot and Villano (2009) undertook a more sophisticated analysis considering also the duration and time of migration, as well as the gender, age, and education of migrants. However, their analysis draws on a rather small dataset of 153 farmers.

Some previous work on farm efficiency in Central and Eastern Europe, based on input-oriented data envelopment analysis (DEA), identifies surpluses (slacks) in input use, so that farms can nonproportionately reduce use of a particular input without harming output. For instance, Latruffe et al. (2005) found that Polish livestock farms in 1996 could have decreased their

Table 1
Summary of previous research on migration and farm technical efficiency/productivity

Author	Data	Method	Measure(s) of migration	Findings
Jokisch (2002)	Ecuador	Farm survey, Chi-square comparison of migrant and nonmigrant households	Dummy variable: household had a member in the United States or not	No significant relationship between migrant status and agricultural productivity
Mochebelele and Winter-Nelson (2000)	Lesotho	Stochastic frontier model	Dummy variable: farms sending migrant to South Africa versus those who did not	Greater technical inefficiency among nonmigrant households
Nonthakot and Villano (2009)	Northern Thailand	Stochastic frontier production function	Number of migrants, gender, education and age migrants, duration, and time of migration	Duration of migration positively impacts on technical efficiency. Number of migrants, time, and gender not significant. Education and age of migrants have positive and negative impact on technical efficiency, respectively
Rozelle et al. (1999)	Northeast China	Regression with dependent variable maize yields	Number of migrants	Migration has significant and negative effect on yields
Taylor and Lopez-Feldman (2010)	Mexico, rural household survey	Migration probit, endogenous switching regression strategy	Dummy variable: household had a member in the United States or not	Higher productivity of land in migrant-household group

utilized land by 3.6% and labor input by 5.8% on average and still achieved the same level of output. However, by the year 2000 such slacks had diminished and Vasiliev et al. (2008) for Estonia also reports a decline in labor slacks for the period 2000–2004. This trend may reflect a correction in labor input following the hoarding of workers by agricultural enterprises during the socialist era. Lissitsa and Odening (2005) report evidence of input slacks for agricultural enterprises in Ukraine but that an increase in workforce per hectare did not necessarily result in a reduction of technical efficiency. The analysis of slacks is complicated however where variations in input quality exist (Thiele and Brodersen, 1999) and cannot be estimated within the approach taken in this article.

3. Kosovo and migration

Kosovo is a small, Western Balkan economy, with an estimated population in 2011 of 1.7 million, of which 92.9% were ethnic Albanian (ASK, 2012b). In 2011, GDP per capita in Kosovo was €2745 (ASK, 2012a). The only European country with a lower level of GDP per capita in this year was Moldova (IMF, 2013).

Over several decades rural Kosovo has witnessed substantial outmigration. Not surprisingly, internal outmigration has been relatively greatest from the poorest regions, whereas there has been an inflow of migrants to more developed regions, particularly the capital city of Pristina (Vathi and Black, 2007). The main source of employment in Pristina is the public sector and related industries, specifically public administration, education, and health (ASK, 2013). In general, there is no agreement on whether migration has changed the educational composition of the labor force in Kosovo, because on average migrants have only completed secondary education (World Bank, 2011; Gashi and Haxhikadrija, 2012).

Estimates of international migration from Kosovo are unreliable. A country report prepared for the European Commission (Gashi and Haxhikadrija, 2012) quotes two estimates, varying from 415,000 to 800,000 migrants (ASK, 2012b). Although it is often claimed that migration from Kosovo was forced because of the military conflict in 1999, a UNDP (2010) survey of the reasons for migration identified that in only 18.2% of cases was the motive related to this, another 23.8% involved other political reasons, but the most important impetus was economic (42.9%). The latter is reflected in the pattern of emigration from Kosovo from the 1960s to 2011: the largest share of emigration (53.6%), took place post conflict (UNDP, 2012).

Male international migrants work across the range of economic sectors including construction, services, tourism and hospitality, and manufacturing (Gashi and Haxhikadrija, 2012), with significant variations depending on the country of destination. Female migrants work mainly in the service sector (39%), manufacturing (26%), and domestic services (18%). Migration is thus not limited to a particular set of skills and few migrants work in agriculture. Permanent return migration has been low—around 3,000 persons in 2011 (Gashi and Haxhikadrija, 2012). The main motivations for return migration have been family reasons, deportation, and homesickness (World Bank, 2011).

Because of its scale, migration (internal and international) has potentially significant ramifications for rural Kosovo, given that 62% of the resident population lives in rural areas and that the share of the labor force engaged in agriculture is 49% (ARCOTRASS, 2006). There is also little evidence that the flow of migration will subside in the near future: a recent UNDP (2012) survey reported that 15% of household heads intended to migrate and in 70% of these cases it was for economic reasons.

4. Data and definition of variables

The data employed in the study were obtained from annual Agricultural Household Surveys conducted by the Statistical Office of Kosovo (SOK) between 2005 and 2008. We constructed an unbalanced panel consisting of 2,217 observations spanning the years 2005 (555 observations), 2006 (495), 2007 (510), and 2008 (657). However, on average a farm is only in the sample for 1.1 years, so that the panel structure is rather weak. As an alternative we therefore estimated cross-sectional specifications. The cross-sectional estimates confirmed the ones obtained by the panel specification, so we therefore concentrate on the latter.

To construct the samples, SOK (2010) applied a two-stage sampling process, first stratifying by region and then by farm size (cultivated area). Within each category, agricultural households were randomly selected for face to face interview. SOK (2010), for the purpose of the survey, defined a household "as a union of persons that live together, and pool their income." Agricultural households were delineated as those that cultivate more than 0.10 hectares (ha) of arable land or less than 0.10 ha of utilized arable land but had at least: one cow or five sheep/goats or three pigs or 50 poultry or 20 beehives.

The annual survey provides, for each household member, information on age, gender, educational attainment, and the number of months, if at all, the family member lived away from the household in the previous 12 months. This was used to calculate migration intensity (the % of total available household work time accounted for by migration). Detailed information, on a plot by plot basis, relating to crops grown, yields, plot sizes, and inputs used were collected.

Outputs included in the multi-output multi-input directional distance function for the estimation of technical efficiency were wheat, hay, potatoes, tomatoes, peppers, and onions. These were chosen because they are the most common products in Kosovo for which a sufficiently large sample (2,217 households out of an initial sample of about 4,000 households) could be built, with all farm households producing some output. The survey collected data relating to the following inputs: land, labor, seeds, fertilizers, plant protection chemicals, fuel, and machinery. Machinery value was estimated as the expected resale value expressed in Euros. All these inputs were included in the distance function. Land was quantified in hectares. The remaining inputs were measured as expenditure in Euros. All input values were deflated.

Kosovo is divided into seven regions (*Ferizaj*, *Gjakove*, *Gjilan*, *Mitrovice*, *Peje*, *Prishtine*, and *Prizren*). Regions were included as dummies to control for differences in agro-environmental conditions and infrastructure. To capture land fragmentation for each farm household, a Simpson Index (SI) was calculated (Blarel et al., 1992). This can be expressed as:

$$1 - \sum_{1}^{i} \frac{A_i^2}{A^2}, \tag{1}$$

where A_i is the area of the ith plot and A is the total farm area. The SI is defined between the values of 0 and 1, where a value of zero indicates no fragmentation of farm land into spatially separated plots. The larger the index score, the greater the level of land fragmentation. Table 2 presents key descriptive statistics for the sample.

The average sampled farm utilized 2.61 ha. Production is very fragmented even compared with neighboring Albania (Deininger et al., 2012) with a mean of 8.38 plots per farm and an SI of 0.75. The majority of land is utilized for wheat and hay production. By Western European standards (European Commission, 2011), farms are poorly capitalized with the total (resale) value of machinery per agricultural household equating to €3,551 in 2005 values. Farming is labor intensive, drawing on input from household members. The use of hired (nonfamily) agricultural labor is minimal.

Part 2 of Table 2 distinguishes between migrant and non-migrant households. Households from which migration has occurred on average operated slightly larger farms: a mean of 2.86 ha compared to 2.39 ha for households, which have not witnessed any migration. The average level of education amongst household members was very similar for both groups. There was also little difference between the two groups in terms of the degree of fragmentation of production. However, the use of tradable inputs (fertilizers, chemicals, seeds, fuel, and machinery) was significantly higher for the migrant household group. Comparing average yields (dividing the land used by production amounts given in Table 2) reveals that they were similar for wheat, potatoes, onions, and tomatoes. In the case of peppers, average yields were higher in the households from which no migration had occurred.

Table 3 details the scale of migration within the sample. Overall, migration is widespread: 45.8% of sampled households have witnessed some degree of migration with, therefore, 54.2% of households not experiencing any migration. Where migration has occurred it is most likely to be limited to one household member. Few households reported high levels of migration intensity, for example it is 50% or higher in only 3.8% of cases. The most common level of migration intensity is between 5% and 10% of total household work time available. Where migration has occurred, however, it tends to be long-term and permanent: the mean length of time that migrants were absent from the household in 2007 and 2008 was 11.2 and 11.1 months, respectively.

5. Empirical modeling

5.1. Directional distance function to evaluate the impact of migration on technical efficiency

A directional output distance function (Chambers et al., 1998; Färe and Primont, 1995) is employed to model technological processes and derive measures of technical (in)efficiency. To measure the efficiency of individual farms, a parametric

Table 2
Descriptive statistics for the sample (Part 1)

Variable	Mean	Minimum	Maximum	SD
All households ($n = 2{,}217$)				
Land area used for wheat production (ha)	1.25	0.0300	150.0	4.007
Land area used for hay production (ha)	1.24	0.0050	30.7	1.729
Land area used for pepper production (ha)	0.03	0.0003	3.0	0.1614
Land area used for tomato production (ha)	0.01	0.0003	0.9	0.0287
Land area used for onion production (ha)	0.02	0.0004	5.2	0.1597
Land area used for potato production (ha)	0.05	0.0004	10.2	0.3087
Share of Male Headed Households (%)	97.56			
Education of household head (level)	3.98	1	9	2.0094
Average age of household members (years)	29.41	13	76.5	7.7184
Average education of household members (category 1–9)	3.36	1.5	7.4	0.8763
Full-time labor per year (no of household members)	1.13	0	21	1.6109
Part-time labor per year (no of household members)	1.50	0	14	1.6646
Utilized land area (ha)	2.61	0.20	151.66	4.6631
Machinery value (in 2005 values in Euro)	3550.64	0	101,826.5	5,759.221
Simpson Index	0.75	0.020	0.941	0.1148
Number of plots	8.38	2	28	3.0827
Wheat production (in kg)	4,562.16	1.25	525,000	13,919.24
Hay production (in kg)	3,561.15	1.15	65,000	5,458.271
Pepper production (in kg)	623.78	3	90,000	3,880.13
Tomato production (in kg)	226.25	4	24,000	937.5705
Onion production (in kg)	226.71	2	97,000	2,244.39
Potato production (in kg)	1,247.03	10	450,000	11,336.87
Fertilizer (in 2005 values in Euro)	352.70	0	16,632	691.8499
Chemicals (in 2005 values in Euro)	47.76	0	3,740	168.3445
Seed (in 2005 values in Euro)	177.09	0	10,000	475.8605
Fuel (in 2005 values in Euro)	265.48	0	15,000	595.2668

Table 2
Descriptive statistics for the sample (Part 2)

	Households with migrant members ($n = 1{,}016$)				Households without migrant members ($n = 1{,}201$)			
Variable	Mean	Minimum	Maximum	SD	Mean	Minimum	Maximum	SD
Land area used for wheat production (ha)	1.48	0.0700	150.0	5.3078	1.06	0.0300	50	2.3984
Land area used for hay production (ha)	1.25	0.0200	30.7	1.7001	1.24	0.0050	21.5	1.7548
Land area used for pepper production (ha)	0.03	0.0003	1.95	0.1401	0.03	0.0005	3	0.1774
Land area used for tomato production (ha)	0.01	0.0003	0.9	0.0365	0.009	0.0004	0.4	0.0197
Land area used for onion production (ha)	0.02	0.0004	5.15	0.2279	0.013	0.0004	1.3	0.0554
Land area used for potato production (ha)	0.05	0.0004	10.2	0.3629	0.05	0.0010	5.1	0.2541
Share of Male Headed Households (%)	97.05				98.01			
Education of household head (level)	3.82	1	11	2.0168	4.12	1	11	1.9942
Average age of household members (years)	28.67	13	76.5	6.7578	30.05	13	76	8.3981
Average education of household members	3.35	1.7	7	0.8381	3.37	1.5	7.375	0.9074
Full-time labor per year (no of household members)	1.29	0	21	1.7657	0.99	0	10	1.4527
Part-time labor per year (no of household members)	1.74	0	14	1.8650	1.29	0	11	1.4432
Utilized land area (ha)	2.86	0.19	151.65	5.8432	2.39	0.23	56.11	3.3431
Machinery value (in 2005 values in Euro)	4,473.76	0	78,104.7	6,399.987	2,769.72	0	10,1826.5	5,027.362
Simpson Index	0.76	0.093	0.9413	0.1098	0.74	0.019	0.9317	0.1178
Number of plots	8.87	4	28	3.3018	7.96	2	23	2.8198
Wheat production (in kg)	5,506.58	4.5	525,000	18,944.32	3,763.21	1.25	195,000	7,268.43
Hay production (in kg)	3,803.22	1.15	65,000	5,811.92	3,356.37	1.25	65,000	5,133.687
Pepper production (in kg)	610.98	5	60,000	3,252.61	634.61	3	90,000	4,342.073
Tomato production (in kg)	255.89	4	23,500	1,038.39	201.18	10	24,000	842.5449
Onion production (in kg)	315.41	5	97,000	3,258.78	151.67	2	10,000	554.4719
Potato production (in kg)	1,381.82	10	450,000	15,024.93	1,132.99	10	120,000	6,809.427
Fertilizer (in 2005 values in Euro)	391.63	0	16,632	883.3212	319.78	0	7,176	470.7272
Chemicals (in 2005 values in Euro)	56.36	0	3,740	197.0513	40.48	0	3,500	139.1964
Seed (in 2005 values in Euro)	214.47	0	10,000	650.5898	145.47	0	3100	240.7654
Fuel (in 2005 values in Euro)	293.57	0	15,000	698.8437	241.72	0	5000	489.9277

Table 3
Extent of migration from farm households

	Number	% of sample
Households from which migration occurred	1,016	45.8
Households without migration	1,201	54.2
Households with one migrant	663	29.9
Households with more than one migrant	353	15.9
Households with up to 5% migration intensity*	31	1.4
Households with ≥ 5 < 10% migration intensity*	401	18.1
Households with ≥ 10 < 15% migration intensity*	84	3.8
Households with ≥ 15 < 20% migration intensity*	86	3.9
Households with ≥ 20 < 30% migration intensity*	160	7.2
Households with ≥ 30 < 40% migration intensity*	112	5.1
Households with ≥ 40 < 50% migration intensity*	56	2.5
Households with ≥ 50 < 60% migration intensity*	58	2.6
Households with ≥ 60 < 90% migration intensity*,†	28	1.2

*Migration intensity expressed as% of total available work time per household per year.
†Because of small numbers of observations we have aggregated households showing a migration intensity of more than 60% and less than 90% into one category.

stochastic frontier approach is used. In this article, the Battese and Coelli (1995) estimator on the distance function is applied using an unbalanced panel data specification. The stochastic specification of the directional output distance frontier takes the form:

$$0 = \vec{D}_0(x, y + \mu g; g) + \varepsilon, \tag{2}$$

where $\varepsilon = v - u$; $v \sim N(0, \sigma_v^2)$ and $u \sim N^+(u, \sigma_u^2)$. To estimate (2), the translation property of the directional output distance function is exploited. Following common practice (Färe et al., 2005), we set $g = 1$, and by rearranging the following equation is obtained:

$$-\mu = \vec{D}_0(x, y + \mu; 1) + \varepsilon. \tag{3}$$

Choosing $\mu = y_1$, which is farm household specific, sufficient variation on the left-hand side is obtained to estimate the specification given in (3). The output vector used is $y =$ (wheat, hay, pepper, tomatoes, onions, and potatoes), whereas the input vector is $x =$ (land, full-time labor, part-time labor, machinery, fuel, rented services, fertilizer, chemicals, and seed). Hence, the final specification estimated is

$$\begin{aligned} -y_w = {} & \alpha_0 + \sum_{i=1}^{M}\left(\alpha_i y_i^{'}\right) + \sum_{i=1}^{M} 0.5\alpha_{ii}\left(y_i^{'}\right)^2 + \sum_{i=1}^{M}\sum_{j=i+1}^{M}\alpha_{ij}\left(y_i^{'}\right)\left(y_i^{'}\right) \\ & + \sum_{i=1}^{N}\left(\beta_i x_i + 0.5\beta_{ii}x_i^2\right) + 0.5\sum_{i=1}^{N}\sum_{j=i+1}^{N}\beta_{ij}x_i x_j + \sum_{i=1}^{M}\sum_{j=1}^{N}\gamma_{ij}\left(y_i^{'}\right) \\ & \times x_j + v - u \end{aligned} \tag{4}$$

where $y_i' = y_i + y_w$ with y_w as the quantity of wheat produced and abstracting from farm household and time-related variation.

The vector of technical inefficiency effects u in the stochastic frontier model outlined in (4) is specified as follows:

$$u = z\delta + w \tag{5}$$

with, according to the conceptual framework, the following components of the vector z: migration intensity, average education of household members, average age of household members, educational level of the head of the household, age of the head of the household, female-to-male ratio within the household, SI, total income, number of plots, region, and year. The selection of these variables is in keeping with previous technical efficiency studies considering small-scale household farms (Hung, et al., 2007; Latruffe and Piet, 2014; Nonthakot and Villano, 2009; Rahman and Rahman, 2009). The random variable w is defined by the truncation of the normal distribution with mean of zero and variance, σ_w^2, such that the point of truncation is $-z\delta$, that is, $w \geq -z\delta$ (see Battese and Coelli, 1995). Abstracting from farm households and time-related variations, technical efficiency is defined by

$$\mathrm{TE} = \exp(-u) = \exp(-z\delta - w). \tag{6}$$

The details of the corresponding likelihood function and its partial derivatives with respect to the individual parameters are presented in Battese and Coelli (1992, 1995). The likelihood function is generally expressed in terms of the variance parameters with σ, $\sigma^2 = \sigma_u^2 + \sigma_v^2$, and γ, $\gamma = \sigma_u^2/\sigma^2$, where $0 < \gamma < 1$.

5.2. Matching estimation approach

The second stage of the empirical analysis consisted of a matching approach to robustly estimate the sample average effect of migration on efficiency as well as the effect for different levels of migration intensity. As farm households are defined by a multitude of different characteristics over space and time, a sophisticated matching approach is required to accurately determine the effect of migration in a statistically robust way (Guo and Fraser, 2010). As we use survey-based nonexperimental data collected through the observation of agricultural household-farming systems as they operate in practice (Rubin, 1997), this type of method allows for reducing multidimensional covariates to a one-dimensional score.

Table 4
Overview of matching models

W_i	Y_i	C_i	N	M	wm	bc	rm
Model 1 "migration intensity" W_{MIG}—level of migration intensity (0—falls not in specific migration category, 1—falls in specific migration category, migration categories: $>0\% \leq 5\%$ of total work time per household (hh) and year used by migrants $>5\% \leq 10\%$ $>10\% \leq 15\%$ $>15\% \leq 20\%$ $>20\% \leq 30\%$ $>30\% \leq 40\%$ $>40\% <= 50\%$ $>50\% \leq 60\%$ $>60\% \leq 90\%$)	Technical efficiency per farm household and year	Age of household head, educational level of household head, average age of household members, average educational level of household members, female-to-male ratio, year dummies for 2006, 2007, and 2008 (year 2005 as reference), regional dummies for Gjakove, Gjilan, Mitrovice, Peje, Prishtine, Prizren (region Ferizaj as reference), number of crops grown, % of crop output marketed, Simpson index, car ownership	2,152	4	Inverse variance	4	10
Model 2 "migration" W_{MIG}—indicator for migration (categories: 0—no migration for hh and year 1—migration for hh and year)	Technical efficiency per farm household and year	Age of household head, educational level of household head, average age of household members, average educational level of household members, female-to-male ratio, year dummies for 2006, 2007, and 2008 (year 2005 as reference) regional dummies for Gjakove, Gjilan, Mitrovice, Peje, Prishtine, Prizren (region Ferizaj as reference), number of crops grown,% of crop output marketed, Simpson index, car ownership	2,152	4	Inverse variance	4	10

W_i, treatment condition; Y_i, indicator variable; N, number of observations; C_i, covariates; M, number of matches; wm, weighting matrix, bc, bias-corrected; rm, number of robust matches.

The underlying framework is Neyman–Rubin's model for causal inference using matching methods (Guo and Fraser, 2010). Farm households, selected into treatment (e.g., migration) and nontreatment groups, have potential outcomes (Y_0, Y_1) in both states ($W = 0{,}1$): the one in which the outcomes are observed ($E[Y_1|W = 1]$, $E[Y_0|W = 0]$) and the one in which the outcomes are not observed ($E[Y_1|W = 0]$, $E[Y_0|W = 1]$). Unobserved potential outcomes that occur under either condition are missing data. A matching estimator directly imputes the missing data at the unit level by using a vector norm. Specifically, it estimates the values of $Y_i(0)|W_i = 1$, that is the potential outcome under the condition of control for the treatment participant, and $Y_i(1)|W_i = 0$ as the potential outcome under the condition of treatment for the control participant. Hence, for each farm the estimator imputes the missing outcome by finding other farm households in the sample whose covariates were similar but which were exposed to the other treatment (e.g., nonmigration).

To ensure that the matching estimator identifies and consistently estimates the migration effect, two assumptions are critical (Abadie and Imbens, 2002). First, conditionally on the covariates, assignment to the migration group is independent of outcomes ("unconfoundedness assumption"). As migration is widespread in Kosovo and, as documented earlier, spread across economic sectors (e.g., public sector, construction, services, tourism and hospitality, and manufacturing) and not biased to a particular skill set, the modeling assumption that assignment to a specific treatment group (migrate or not) is independent of outcomes (technical efficiency of the farm) appears reasonable. Second, we assume that the probability of assignment is bounded away from 0 and 1, that is there is sufficient overlap in the distribution of observed covariates ("identification assumption"; Abadie and Imbens, 2011). The central challenge is the dimensionality of covariates or matching variables, because as their number increases, the difficulty of finding matches for treated farm households also rises. Matching estimators use the vector norm to calculate distances on observed covariates between a treated case and each of its potential control cases (i.e., counterfactuals).

Let us consider the set of observed covariates for farm i, C_i, and the vector norm with positive definite matrix V defined as $cv = (c' V c)^{1/2}$. The distance between the vectors c and q, with the latter representing the covariate values for a potential match

Table 5
Directional output distance frontier estimates

Variable	Coefficient	t-statistics
Pepper output	1.17e-05***	6.34
Hay output	−1.22e−06**	−2.43
Tomato output	−6.42e−05***	−11.47
Onion output	−1.57e−04***	−27.71
Potato output	−8.07e−06***	−5.24
Land	5.43e−04	0.21
Labor ft (full-time)	0.002**	2.14
Labor pt (part-time)	0.006***	3.43
Machinery	−9.74e−07	−1.44
Fuel	2.04e−05*	1.80
Rentals (land/buildings)	−1.83e−05	−1.16
Fertilizers	4.24e−06**	2.30
Chemicals	2.82e−04***	5.80
Seeds	3.11e−06***	3.17
Pepper^2	0.011***	5.40
Hay^2	−0.002	−0.85
Tomato^2	0.156***	14.66
Onion^2	0.092***	9.05
Potato^2	−8.07e−06***	−5.24
Land^2	−8.85e−04***	4.61
Labor ft (full-time)^2	−3.37e−04*	−1.90
Labor pt (part-time)^2	−3.67e−04***	−8.52
Machinery^2	−2.279e−04	−1.14
Fuel^2	3.68e−05**	2.19
Rentals (land/buildings)^2	−2.87e−05	−0.14
Fertilizers^2	1.91e−04***	3.17
Chemicals^2	−6.31e−04***	−7.00
Seeds^2	−0.002***	−3.34
Hay × pepper	−0.028*	−1.83
Hay × tomato	−0.007	−0.27
Hay × onion	0.057**	2.15
Hay × potato	−0.033**	−2.78
Pepper × tomato	0.004	0.38
Pepper × onion	−0.053***	−3.02
Pepper × potato	0.023***	4.56
Tomato × onion	−0.183***	−9.18
Tomato × potato	−0.009	−0.98
Onion × potato	−0.035***	−6.04
Land × labor ft	−0.003*	−1.84
Land × labor pt	−0.002	−0.83
Land × machinery	−0.008***	−3.76
Land × fuel	−0.002***	4.34
Land × rentals	0.002	0.58
Land × fertilizers	0.005*	1.81
Land × chemicals	−0.002	−1.07
Land × seeds	−2.32e−04***	−9.20
Labor ft × labor pt	−1.46e−04***	−2.40
Labor ft × machinery	−0.002***	−2.34
Labor ft × fuel	0.001*	1.86
Labor ft × rentals	−9.05e−04	−1.06
Labor ft × fertilizer	9.81e−04	0.61
Labor ft × chemicals	−0.002***	−2.73
Labor ft × seed	−0.002***	−2.23
Labor pt × machinery	0.003**	2.27
Labor pt × fuel	0.001	1.08
Labor pt × rentals	−7.89e−04	−0.67
Labor pt × fertilizer	0.007***	3.23
Labor pt × chemicals	0.001	1.34
Labor pt × seed	−0.004	−3.29
Machinery × fuel	−5.04e−04	−0.96
Machinery × rentals	−0.001*	−180
Machinery × fertilizer	0.008***	5.29
Machinery × chemicals	−0.002***	−3.25
Machinery × seed	0.005***	5.20
Fuel × rentals	0.003***	3.55
Fuel × fertilizer	−0.002*	−1.97
Fuel × chemicals	2.56e−04	0.55
Fuel × seed	−0.002***	−4.15
Rentals × fertilizer	−0.003*	−1.80
Rentals × chemicals	1.89e−04	0.27
Rentals × seed	−9.21e−04*	−1.81
Fertilizer × chemicals	9.83e−04*	1.91
Chemicals × seed	0.001**	2.51
Hay × land	0.008**	2.22
Hay × labor ft	0.003*	1.83
Hay × labor pt	−0.002	−0.90
Hay × machinery	0.006***	2.94
Hay × fuel	0.001	0.57
Hay × rentals	−8.51e-04	−0.39
Hay × fertilizers	−0.017***	−4.34
Hay × chemicals	0.006***	2.87
Hay × seeds	0.012***	4.65
Pepper × land	0.035***	3.30
Pepper × labor ft	0.002*	1.91
Pepper × labor pt	−0.038***	−10.63
Pepper × machinery	0.007*	1.84
Pepper × fuel	−0.003***	−2.73
Pepper × rentals	0.008***	3.98
Pepper × fertilizers	−0.021***	−8.64
Pepper × chemicals	−0.005**	−2.28
Pepper × seeds	−0.012***	−6.19
Tomato × land	−0.306***	−9.59
Tomato × labor ft	0.069***	9.24
Tomato × labor pt	−0.087***	−6.48
Tomato × machinery	0.128***	12.50
Tomato × fuel	−0.121***	−14.50
Tomato × rentals	−0.002	−0.18
Tomato × fertilizers	0.006	0.63
Tomato × chemicals	0.071***	12.15
Tomato × seeds	−0.084***	−6.31
Onion × land	0.252***	8.94
Onion × labor ft	−0.093***	−11.97
Onion × labor pt	0.138***	10.10
Onion × machinery	−0.157***	−15.43
Onion × fuel	0.146***	16.03
Onion × rentals	−0.023*	−1.93
Onion × fertilizers	−0.032***	−3.03
Onion × chemicals	−0.049***	−11.09
Onion × seeds	0.067***	5.20
Potato × land	0.026**	2.41
Potato × labor ft	0.030***	11.92
Potato × labor pt	−0.023***	−6.58
Potato × machinery	0.021***	7.07
Potato × fuel	−0.027***	−13.25
Potato × rentals	0.024***	7.18
Potato × fertilizers	0.055***	12.87
Potato × chemicals	−0.023***	−17.16
Potato × seeds	0.021***	14.25
Time	0.002*	1.90
Time × time	−1.02e−04***	−13.57
Constant	0.011**	2.31

Continued

Table 5
Continued

Technical efficiency	Mean	SD	Min	Max
Full sample	0.611***	0.243	0.012	0.981
Households with no migration	0.644***	0.231	0.012	0.981
Households with migration	0.571***	0.251	0.032	0.978
γ	0.819***			
σ	0.00596***			
σ^2 (v)	0.00108			
σ^2 (u)	0.00488			
Log-likelihood function	3,498.377			
Number of observations = 2,163				

*10%, **5%, ***1% significance.

for farm i, can be defined as $q - cv$. $d_M(i)$ is the distance from the covariates for farm i, C_i, to the Mth nearest match with no migration satisfying:

$$\sum_{l:W_l=1-W_i} 1\left\{C_l - C_i v < d_M(i)\right\} < M$$

and

$$\sum_{l:W_l=1-W_i} 1\left\{C_l - C_i v \le d_M(i)\right\} \ge M \tag{7}$$

and with $1\{\cdot\}$ as the indicator function, which is equal to one if the expression in brackets is true and zero otherwise (Abadie et al. 2004). Let then $J_M(i)$ denote the set of indices for the matches for farm i that are at least as close as the Mth match

$$J_M(i) = \{l = 1, \ldots, N \mid W_l = 1 - W_i, ||C_l - C_i||v \le d_M(i)\}. \tag{8}$$

Finally, the number of elements of $J_M(i)$ is $\#J_M(i)$ and $K_M(i)$ is the number of times farm i is used as a match for all observations l of the opposite treatment group weighted by the total number of matches for observation l

$$K_M(i) = \sum_{l=1}^{N} 1\{i \in J_M(l)\} \frac{1}{\#J_M(l)}. \tag{9}$$

The simple matching estimator estimates the pair of potential outcomes as:

$$\hat{Y}_i(0) = \begin{cases} Y_i & \text{if } W_i = 0 \\ \frac{1}{\#J_M(i)} \sum_{l \in J_M(i)} Y_l & \text{if } W_i = 1 \end{cases}$$

and

$$\hat{Y}_i(1) = \begin{cases} \frac{1}{\#J_M(i)} \sum_{l \in J_M(i)} Y_l & \text{if } W_i = 0 \\ Y_i & \text{if } W_i = 1, \end{cases} \tag{10}$$

where the unobserved outcome is estimated by averaging the observed outcomes for the observations l of the opposite treatment group that are chosen as matches for farm i. Based on these estimates, the matching estimator for various treatment effects (i.e., migration levels) is:

$$\hat{\tau}_M^{me} = \frac{1}{N}\sum_{i=1}^{N}\left\{\hat{Y}_i(1) - \hat{Y}_i(0)\right\} = \frac{1}{N}\sum_{i=1}^{N}(2W_i - 1)\{1 + K_M(i)\}Y_i \tag{11}$$

and modified for the estimation of the average treatment effect for the treated farms

$$\hat{\tau}_M^{me,t} = \frac{1}{N_1}\sum_{i:W_{i=1}}\left\{Y_i - \hat{Y}_i(0)\right\} = \frac{1}{N_1}\sum_{i=1}^{N}\{W_i - (1 - W_i)K_M(i)\}Y_i. \tag{12}$$

Abadie et al. (2004) recommend using four matches for each unit since the drawback of using only one match is that the process uses too little information in matching. In finite samples, the outlined matching estimator might be biased when matching is not exact. Following Abadie and Imbens (2002), we therefore adjust the difference within the matches for the differences in their covariate value whereby the adjustment is based on the estimates of the linear regression functions $\mu_w(c) = E\{Y(w) | C = c\}$ for $w = 0$ or 1 using the matched observations. For the sample average treatment effect we estimate the regression:

$$\hat{\mu}_w(c) = \hat{\beta}_{w0} + \widehat{\beta'}_{w1}c, \tag{13}$$

for $w = 0,1$, where

$$\left(\hat{\beta}_{w0}, \hat{\beta}_{w1}\right) = argmin_{\{\beta_{w0},\beta_{w1}\}} \sum_{i:W_{1=w}} K_M(i)\left(Y_i - \beta_{w0} - \beta'_{w1}C_i\right)^2, \tag{14}$$

where $K_M(i)$ is used as a weight. The bias-corrected matching estimator for the average treatment effect is then:

$$\hat{\tau}_M^{bcm} = \frac{1}{N}\sum_{i=1}^{N}\left\{\hat{Y}_i(1) - \hat{Y}_i(0)\right\} \tag{15}$$

with the missing potential outcomes being:

$$\hat{Y}_i(0) = \begin{cases} Y_i & \text{if } W_i = 0 \\ \frac{1}{\#J_M(i)} \sum_{l \in J_M(i)} \{Y_l + \hat{\mu}_0(C_i) - \hat{\mu}_0(C_l)\} & \text{if } W_i = 1 \end{cases}$$

and

$$\hat{Y}_i(1) = \begin{cases} \frac{1}{\#J_M(i)} \sum_{l \in J_M(i)} \{Y_l + \hat{\mu}_1(C_i) - \hat{\mu}_1(C_l)\} & \text{if } W_i = 0 \\ Y_i & \text{if } W_i = 1. \end{cases} \tag{16}$$

Finally, the assumption of a constant treatment and homoscedasticity may not be valid for certain types of covariates. To account for such potential heteroskedasticity, we use a second matching procedure, matching treated units to treated units and control to control cases based on a variance

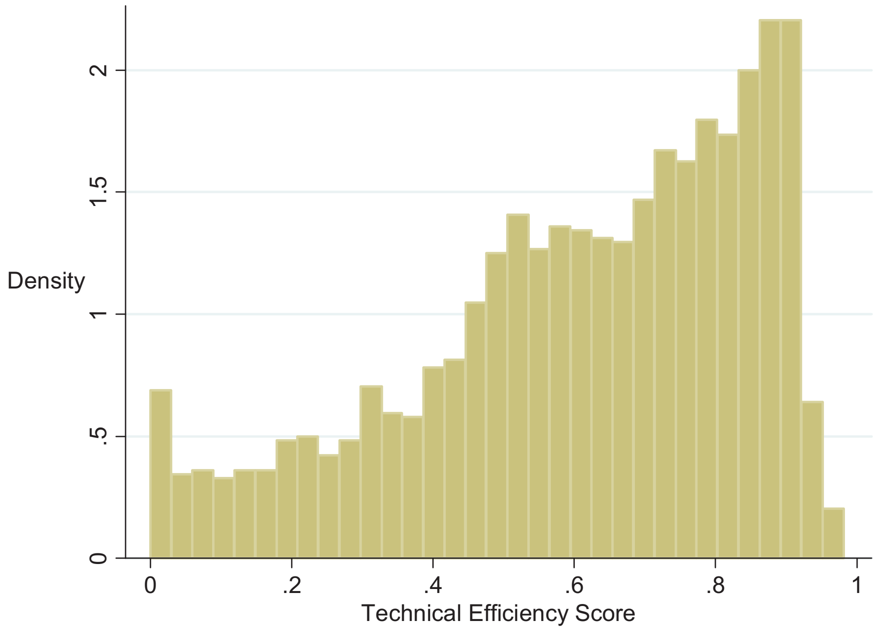

Fig. 1. Density distribution of technical efficiency scores.

estimation (Abadie et al., 2004). The variance estimator for the sample average treatment effect is

$$\hat{V}^{\text{sample}} = \frac{1}{N^2} \sum_{i=1}^{N} \{1 + K_M(i)\}^2 \, \hat{\sigma}^2_{W_i}(C_i)\,. \tag{17}$$

Assuming that $\sigma^2_w(c)$ varies by treatment w and covariate c, the conditional variance is estimated as the sample variance given in (24) augmented with the outcome for farm i itself, $J'_M(i) \cup (i)$:

$$\tilde{\sigma}^2_{W_i}(C_i) = \frac{1}{\# J'_M(i)} \sum_{j \in \left\{ J'_M(i) \cup (i) \right\}} \left\{ Y_i - \bar{Y}_{J'_M(i) \cup (i)} \right\}^2, \tag{18}$$

where $\bar{Y}_{J'_M(i) \cup (i)}$ is the average outcome in this set (Abadie et al., 2004). Table 4 summarizes the two matching models estimated. The efficiency scores obtained from the frontier model are used as outcome variables, whereas the different levels of migration intensities are used as indicator variables. As the estimation of the efficiency scores is based on input variables that are not used as matching controls but simultaneously are estimated also as a function of migration related variables, there is no inconsistency or bias related to this procedure.

The efficiency estimation is based on the assumption that the level of inefficiency is not independent of migration, which is then the basic assumption for the matching estimations using the efficiency scores as outcome variables. We use the following variables as matching controls: the age of the head of the household, the educational level of the head of the household, the average age and educational level of household members, the female-to-male ratio per household, year and region dummies, the SI to indicate the degree to which production is fragmented, measures to control for the degree of specialization and market integration of production, and finally a simple dummy to indicate whether the specific household owns a car. Specialization was measured in terms of the number of crops grown whereas market integration was measured as the percentage of crop output that was sold (i.e., not subsistence production). Collectively, these variables serve the purpose of matching treated (i.e., migration affected) households as accurately as possible with nontreated households in the sample.

6. Results

The overall quality of the estimated distance frontier and the estimated matching models are largely satisfactory, indicating the robustness of our empirical results. Table 5 reports the estimates for the directional output distance frontier function that gives the technical efficiency scores at household level. Fig. 1 summarizes the distribution of technical efficiency scores. The mean efficiency for the whole sample has been estimated at 61.1% with a standard deviation of 24.3%, a minimum of 1.2% and maximum of 98.1%. The majority of farms in the sample show a technical efficiency level of more than 50%. The distribution of technical efficiency scores is similar to that reported for other emerging economies (Nonthakot and Villano, 2009). Distinguishing between those households with and without migration reveals a significant difference. The mean efficiency of households without any migration is 64.4%, whereas the comparable figure for households that have experienced migration is 57.1%.

Table 6
Determinants of inefficiency

Determinant	Coefficient	*t*-statistic
Migration intensity (% of total available work time per household, per year)	0.729***	3.26
Migration intensity × Migration intensity	1.186***	4.06
Migration intensity × Educational level of household members	0.061***	6.93
Migration intensity × Average age of household members	0.011***	3.61
Migration intensity × Female-to-male-ratio	0.178**	2.12
Migration intensity × Total income	0.000	3.09
Migration intensity × Cattle	−0.093	−1.07
Migration intensity × Farm equipment	0.000	0.60
Average educational level of household members	−0.219***	−3.93
Average age of household members	0.051***	7.71
Educational level of household head	−0.254***	−11.23
Age of household head	0.018***	6.40
Female-to-male ratio	0.083*	1.94
Farm equipment/machinery (in 1,000 Euro)	−1.24e-04***	−18.73
Total income	0.000	−0.47
Cattle	0.025	1.11
Children-to-adult ratio	0.372***	3.10
Simpson index (SI)	11.739***	22.68
Number of plots	0.457***	23.44
Product diversity index	0.031***	3.39
Region Ferizai	−0.283***	−2.19
Region Prizren	−0.578***	−5.49
Region Gjakove	−0.684***	−5.21
Region Peje	−0.350***	−3.05
Region Mitrovice	0.492***	4.15
Region Prishtine	−0.789***	−6.51
Year 2006	−0.301***	−3.02
Year 2007	−0.979***	−9.56
Year 2008	−0.314***	−3.31
Constant	9.998***	19.99

*10%, **5%, and ***1% significance; benchmark year: 2005; benchmark region: Gjilan.

The overall model quality of the estimated distance frontier was evaluated using the estimated values for γ and σ. The highly significant estimate for γ indicates that much of the variation in the composite error term is because of the inefficiency component. The highly significant estimate for σ suggests that the consideration of production inefficiency plays a significant part in explaining households' production behavior. Different alternative frontier specifications with respect to functional form (i.e., Cobb–Douglas vs. Translog) and explanatory variables (i.e., a reduced form excluding cross-terms as well as the consideration of biased technological change related terms) were estimated with the most appropriate selected based on various Lagrange multiplier test statistics and the relative values for the Akaike Information Criterion.

Table 6 presents the estimations for the determinants of inefficiency. Migration intensity (based on % of total available work time per household per year) has an efficiency decreasing effect. This effect is highly significant even when region, year, socioeconomic characteristics of the household (age, education, gender, income), and farm characteristics (number of plots, cattle, etc.) are accounted for.

Regarding other additive terms, fragmentation of production, captured by both the SI, and the number of plots, has a significant, negative effect on efficiency. This is consistent with recent findings on small-scale agriculture in Bangladesh (Rahman and Rahman, 2009), Bulgaria (Di Falco et al., 2010), and Vietnam (Hung et al., 2007). Moreover, both human capital (approximated by education) and physical capital (farm equipment) decrease technical inefficiency. The finding for education is in keeping with the estimations of Nonthakot and Villano (2009). From this point of view it is disappointing that, according to UNDP (2012), only 4.6% of remittances are used for investment in education and 3.9% for business investment, including 0.8% for purchase of land. Total household income is not a significant determinant of technical efficiency.

The interaction effects indicate that the efficiency decreasing effect of migration is amplified in the case of better-educated and older households (the latter measured by the average age of household members) and where the female-to-male ratio within the household is higher. This indicates that migration may have a particularly negative effect on technical efficiency in households with few males (i.e., with a high female-to-male ratio) and few young adults. This is important given that young males have the highest propensity to migrate. As the female-to-male ratio has a negative impact on technical efficiency, the loss of the only male worker (interactive term) has a particularly negative impact on technical efficiency. The loss a young adult within a household characterized by elderly adults has a similar effect. The loss of better educated workers is aggravated by the reliance on family labor and lack of use of hired in labor. This implies that educated migrants are not effectively replaced on farm. The variable (migration intensity × migration intensity) provides a check for the matching estimations discussed below and is consistent with these findings—there is significant and positive effect on technical inefficiency.

Table 7 reports the sample average treatment effects for changes in technical efficiency at the household level for different levels of migration intensity. The results indicate that the impact of migration on technical efficiency is consistently negative across different levels of migration intensity, apart from intensities between 15% and 20%, 30% and 40%, as well as 50–60%. The negative impact on technical efficiency is greatest for those households with the highest level of migration intensity, namely where migration accounts for between 60% and 90% of total available work time of the household in a particular year.

The results indicate that migration has a significant, efficiency lowering effect even at low levels of intensity. This includes where migration accounts for 5 or less percent of total available work time per household in a particular year. Given the labor intensive nature of farming in Kosovo and the absence of perfect substitutes, with no hired in nonfamily workers, even relatively small levels of migration negatively affect technical efficiency.

The statistical quality of the estimated matching models is indicated by the significance of the treatment effects based on

Table 7
Sample average treatment effects (SATE) for different levels of migration intensity

Migration intensity (% of total available work time per hh and year used by migrants)	Change in technical efficiency because of migration at household level (SATE)		
	Mean	Min	Max
0% ≥ 5%	−0.143***	−0.249	−0.036
5% ≥ 10%	−0.023**	−0.062	−0.052
10% ≥ 15%	−0.058*	−0.123	0.006
15% ≥ 20%	−0.032	−0.009	0.025
20% ≥ 30%	−0.037**	−0.086	0.012
30% ≥ 40%	−0.012	−0.065	0.042
40% ≥ 50%	−0.057**	−0.131	−0.002
50% ≥ 60%	0.015	−0.074	0.104
60% ≥ 90%	−0.183***	−0.297	−0.071
Migration (yes/no)	−0.042***	−0.065	−0.018

*, **, and *** denote statistical significant at 10%, 5%, 1% level based on AI robust standard errors.

Table 8
Robustness checks for matching models (exemplary for migration [yes/no])

Distance tolerance (limit imposed for distance)	Treatment effect		Overlap check (no. of observations that violate the overlap assumption)
	Coefficient	AI robust SE	
Distance metric I: Mahalanobis (inverse sample covariate covariance)			
0.0005	−0.042***	0.012	0
0.005	−0.041***	0.011	0
0.05	−0.041***	0.011	0
0.5	−0.046*	0.024	0
1.0	−0.047***	0.013	0
Distance metric II: inverse variance (inverse diagonal sample covariate covariance)			
0.0005	−0.039***	0.011	0
0.005	−0.039***	0.012	0
0.05	−0.041***	0.012	0
0.5	−0.051*	0.027	0
1.0	−0.049***	0.013	0
Distance metric III: Euclidean (identity)			
0.0005	−0.051***	0.011	0
0.005	−0.051***	0.010	0
0.05	−0.051***	0.011	0
0.5	−0.051*	0.026	0
1.0	−0.058*	0.031	0

*, **, and *** denote statistical significant at 10%, 5%, and 1% level, respectively.
Similar robustness checks for all other estimated treatments with respect to migration shares confirm the statistical quality of the estimated migration effects. These are not reported here because of limitations of space.

the Abadie–Imbens robust standard errors. This follows Abadie and Imbens (2008), who demonstrate that bootstrap-based estimators do not provide reliable standard errors for the average nearest-neighbor matching case. To further check the reliability of the matching estimator chosen, the various treatment effects were estimated using alternative distance metrics. The estimated treatment effects vary only minimally in magnitude and statistical significance. To ensure that households that are too different are not matched, limits for the distance tolerances were imposed. Finally, the assumption of sufficient overlap in the distribution of observed covariates was tested for by determining the number of observations that violate this assumption. Table 8 summarizes the results of the robustness checks with respect to the overall migration treatment (i.e., migration “yes” or “no”). Similar robustness tests have been conducted for all other matching models, which largely confirmed the statistical quality of the applied matching procedure.

7. Conclusions

Rural outmigration in Kosovo, as in many emerging and transitional economies, has been widespread and this article tackles the important question of the impact of such migration on farm efficiency. The article extends previous analysis by calculating migration intensity (rather than relying on crude, dichotomous measures of whether migration occurred or not) and applying a two-stage estimation procedure (Frontier technique followed by a matching estimation approach).

The analysis identifies that there is a significant and negative “lost labor effect” on farm efficiency. The negative effect of migration on technical efficiency is amplified for households with better educated family workers. This suggests the presence of labor market imperfections with farm households relying also exclusively on family labor. Although remittances may partially compensate for the lost labor effect in some cases (Taylor et al., 2003), for Kosovo total household income is not a significant determinant of technical efficiency and the proportion of remittances spent on upgrading human and physical capital appears small (UNDP, 2012). Migration has a significant negative effect on technical efficiency even at low levels of intensity but is greatest for the highest category of migration intensity (migration accounts for 60–90% of total available work time of the household in a particular year). Overall, the findings for Kosovo indicate a significant, adverse effect of migration on farm technical efficiency.

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