Influence of milk yield on profitability – a quantile regression analysis

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Abstract:

The paper analyses factors influencing the economic success of Swiss dairy farms, measured by annual income per family work unit, using panel-data regression techniques. Based on more than 5400 observations, the analysis focusses on annual milk yield per cow as key explanatory variable, adjustable by the farm manager in the medium term. We apply a random-effects model and a quantile regression based on deciles, which allows us to study the heterogeneity of the sample in more detail. Consistently with literature, the random-effects model shows a positive contribution of milk yield: an additional ton per cow results in an increase of CHF 2660, i.e. 6% of annual income. The quantile regression reveals that the impact of milk yield differs between deciles: a high milk yield is most beneficial for the best performing farms, accounting for up to 7210 CHF per ton. Our analysis further shows the influence of milk yield on profitability to be highly heterogeneous among Swiss dairy farms, indicating the demand for business-specific consulting services and not indicating the requirement for increased milk yield at each level of economic success. Key words: dairy, milk yield, quantile regression, random-effects model, Switzerland, financial performance

Acknowledegment: The authors are grateful to the FADN team of Agroscope for providing the data and to Nadja El-Benni and Swetlana Renner for comments.

JEL Codes: Q14, Q12

#535

Jan. 4, 2018

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INTRODUCTION

Besides cattle genetics, breeding objectives, and feed composition, milk yield is a key element of milk production systems. Higher milk yield is usually associated with more intensive production, higher gross margins per area managed, but also higher costs, e.g. of concentrate input (Nix, 2015). Given that in the medium run, the farm manager can adjust milk yield to some extent, the influence of milk yield on profitability is of high interest.

It is thus frequently analyzed in the literature, typically by a regression model, and generally considered positive. Vandehaar (1997) argues that for US dairy farms even beyond a boundary of digestive efficiency of cattle, a positive relationship between milk yield and farm profitability persists. Winsten et al. (2000) show by a multiple regression that milk production per cow is critically important for the profitability of dairy farms in the Northeastern US[1]. Ford and Shonkwiler (1994) conclude that milk sold per cow and farm size in livestock units (**LU**) positively affect net farm income of Pennsylvanian dairy farms, with milk per cow having the stronger influence. For New York dairy farms, two analyses (Kauffman and Tauer, 1986, and Gloy et al., 2002) find a positive impact of milk yield on return on assets.

Hoop et al. (2015) examine determinants of production costs for one kilogram of milk for combined Swiss dairy and arable crop farms showing that milk yield per cow reduces costs.

As Swiss dairy farms are mostly family-operated, annual income per family working unit (**FWU**) is a suitable indicator for economic performance. Roesch (2015) analyses the success of Swiss dairy farms by this indicator, while Mishra and Morehart (2001) use a similar measure for their analysis of US dairy farms.

Income data of Swiss dairy farms reveal substantial heterogeneity. In 2014, mean income per FWU of the lowest-performing quarter was CHF 14,200, while that of the highest quarter was CHF 70,000 or five times as much (cf. Dux et al., 2016).

Quantile regression (**QR**) allows to analyze different levels of the dependent variable, in our case annual income per **FWU**, and has been used in farm management research for some time (Chidmi et al., 2011; El Osta, 2011; Bakucs et al., 2013; Khanal and Mishra, 2016; Tauer, 2016; Hadrich et al., 2017).

[1] for confinement feeding, management-intensive grazing and mixed production systems

We examine the influence of milk yield as one of several independent variables on income per FWU. We perform a two-fold analysis, comparing a random-effects model with a panel-based QR approach. To our knowledge, this combination is new to literature; similar analyses have been restricted to single-year regressions and a set of variables less focused on production (cf. Hadrich et al., 2017). Our approach assesses whether using QR provides additional insights.

We address two additional issues. First, we introduce concentrate input as an explanatory variable, reflecting its increase in Swiss milk production during the last decade (cf. Erdin and Giuliani, 2011). Secondly, we address education in a wider context than in earlier literature, including education of the farm manager and his or her partner in the agricultural, housekeeping and other industrial sectors.

The paper is organized as follows: Section 2 describes our models and data, and formulates hypotheses. Section 3 details the results of our two-fold regression analysis, pointing out similarities between the models and additional insights gained by QR. Section 4 discusses results based on our hypotheses of Section 2, while Section 5 concludes.

MATERIALS AND METHODS

Data Source

We base our analysis on the Swiss Farm Accountancy Data Network (**FADN**) which annually collects data from more than three thousand farm operations to assess the economic situation of Swiss agriculture. Data are based on operational accounting using direct costing. We focus on specialized dairy farms for the years 2010 to 2014. During this period, no significant changes in Swiss agricultural policy occurred for these farms. The resulting set of unbalanced panel data comprises 5’459 observations split between 1’832 farms, with an average of three observations per farm. Key information about the sample is provided in Table 1, including the mean values of decile intervals ordered by annual income per FWU[2].

Table 1: Mean values of decile intervals of the relevant explained and explanatory variables

Variable	Unit	Mean	Mean of decile intervals									
			1	2	3	4	5	6	7	8	9	10
Annual income per FWU	kCHF	**42.8**	-7.7	14.4	22.7	29.6	36.0	42.8	50.0	59.6	73.6	107.6
Utilized agricultural area	ha	**23.1**	18.3	17.9	19.0	20.7	22.1	23.4	24.2	25.1	27.6	32.3
Number of livestock	LU	**30.3**	25.1	22.6	24.8	26.1	28.3	30.3	31.5	33.0	36.8	44.8
Milk yield	t/LU/a	**6.41**	6.19	6.02	6.2	6.21	6.37	6.46	6.46	6.65	6.64	6.91

On average, income per FWU amounts to CHF 42’800[3], and a farm has 30.3 LU, 23.1 hectares of utilized agricultural area and an average milk yield per cow of 6410 kg. With decile intervals being ordered by annual income, all variables show an increasing tendency[4].

Dependent variable: Annual income per FWU as a measure of financial performance

Indicators for a farm’s economic performance vary widely throughout literature. Net farm income has been used as an indicator by Ford and Shonkwiler (1994) and Hadrich et al. (2017). Mishra and Morehart (2001) argue this figure to indicate longer-term survival of the farm. Net farm income still comprises remuneration of the family’s own labor and capital. Deducting opportunity costs for the remuneration of capital and dividing by the number of FWU, annual income per FWU results. At current interest rates, remuneration of labor exceeds remuneration of capital by sixteen times (Lips and Gazzarin, 2016) for Swiss farms. This and the importance of FWU as owners and managers of dairy farms underscores the importance of income per FWU for Swiss agriculture.

Choice of explanatory variables and hypotheses

Based on literature, we formulate hypotheses and define six sets of variables used to explain economic performance of Swiss dairy farmers[5].

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[2] If each year comprised 100 observations, the value attached to the 3[d] decile would be the mean of the respective variables attached to the 21[st]-largest to the 30[th]-largest observations of income per FWU – e.g. the number of LU attached to these income figures.

[3] Average exchange rates (2016) are 1 CHF = 0.86 Euro = 1.01 USD, https://data.snb.ch, accessed 23 November 2017.

[4] Two out of ten times, the subsequent quantile mean is allowed to be less than the preceding one.

[5] Swiss FADN data contains several hundred time series, so we have to rely on literature to narrow down our set of variables.

The first set reflects the structural situation (set **S: 7**). Based on Kaufman and Tauer (1986), Ford and Shonkwiler (1994), Roesch (2015) and Hadrich et al. (2017), we hypothesize that farm size in LU impacts profitability positively. Based on Roesch (2015), farm area (total farmland owned, natural and artificial grassland), share of rented to total farmland, and stocking density may positively influence profitability. Farm location in steep terrain triggers subsidies according to Swiss agricultural policy which may influence income negatively (higher costs) or positively (additional direct payments).

The second set of regional dummies (set **R: 7**) comprises the location of the farm within one of Switzerland's macro-regions[6] (cf. BFS, 1999) or a mountain canton[7] (cf. RKGK, 2017). We use these variables to filter out regional differences.

Production technique (set **P: 6**) is addressed by milk price per unit of milk, milk yield per LU, organic production, free-stall housing, silage-free production and cost of concentrate feed per dairy cow. Based on Kauffman and Tauer (1986), Gloy et al. (2002), Winsten et al. (2000) and Vandehaar (1997) we expect a positive contribution of milk yield to the dairy farm's economic performance. Purchased feed affects income negatively, according to Kauffman and Tauer (1986), leading to our hypothesis that this is also the case for concentrate input. Results concerning organic farming (Khanal and Mishra, 2016; Hadrich et al., 2017) are mixed.

We consider three different aspects of diversification (set **D: 3**) using inverse normalized Herfindahl-Hirschman indices (H_i^n) based on Hirschman (1964)[8].

The first index $H_{i,tot}^{n=3}$ measures a farm's total diversification outside the dairying sector. It is constructed based on aggregated revenues from livestock-related farming except dairying, cropping-related activities, and agriculture-related activities. The second index

[6] CH01 – South-Western Switzerland (Geneva, Vaud and Valais); CH02 – "Espace Mittelland" (Berne, Solothurn, Fribourg, Neuchâtel, Jura); CH03 – Northwestern Switzerland (two half-cantons of Basel, Aargau); CH04 – Zurich; CH05 – Eastern Switzerland (Thurgau, St. Gall, Schaffhausen, Grisons, Glarus, two half-cantons of Appenzell); CH06 – Central Switzerland (Lucerne, Zug, Obwalden, Nidwalden, Uri, Schwyz); CH07 – Ticino. There are no data within the sample for the Ticino macro-region.

[7] Mountain cantons (RKGK, 2017) comprise Glarus, Nidwalden, Obwalden, Uri, Grisons, Ticino and Valais.

[8] Construction of the diversification index is described in the Appendix.

$H_{i,pl}^{n=13}$ [9] measures diversification within crop-related activities (i.e. following several activities instead of just one aggregated one as in the first index). The third index $H_{i,ar}^{n=4}$ applies to agriculture-related activities comprising direct sales, agricultural work for third-parties, agritourism and other activities.

Mishra and Morehart (2001) find overall diversification to negatively affect a farm's economic success, as does Roesch (2015) for aspects of diversification within cropping, and Khanal and Mishra (2016) for agriculture-related activities. Hence, for our three aspects of diversification, we expect a negative contribution to a farm's economic success.

Another set of variables comprises organizational and financial factors of the farm business (set **O: 4**): the share of farm to total income available[10], the share of non-family working units (**non-FWU**) as a percentage of total working units, the size of the farm operator's household, as well as a capitalization index. The latter is constructed as the ratio of costs for equipment, building and machinery, including depreciation, divided by all except personnel costs.

We expect full-time farming to positively affect income (cf. Khanal and Mishra, 2016), and the number of workers (cf. Roesch, 2015) – in our case the non-FWU as well as the size of the operator's family – to contribute negatively. Mishra and Morehart (2001), moreover, find capitalization to have a negative, if statistically insignificant, impact on a farm's economic success.

A final set of twenty-two variables (set **E: 22**) addresses education of the farm operator and his or her partner. Three areas of education – agriculture, housekeeping and all remaining sectors – are combined with five levels of attainment for agriculture and three levels for each of the remaining two sectors[11]. We hypothesize a positive contribution of a high level of

[9] Here, n = 13, including revenues from bread and fodder cereal, maize, potatoes, sugar beets, rapeseed, fresh and canned vegetables, fruits and vine, tobacco, roughage, other crops and forestry.

[10] This is normalized to the interval zero to unity being set equal to zero if farm income is negative, and equal to unity if non-farm income is negative.

[11] Note that in a combination of variables related to education, a single variable quickly loses its significance. The five distinct levels of education are no apprenticeship, started apprenticeship, finished apprenticeship,

education (cf. Mishra and Morehart, 2001; El Osta, 2011; Khanal and Mishra, 2016; Hadrich et al., 2017), a negative one for a low level (cf. Hadrich et al., 2017).

Our set of explanatory variables comprises forty-nine in total.

Climate, soil and weather data, as well as genetic resources of each farm's dairy cattle are outside the scope of our study, as they cannot easily be linked to FADN data. For cattle genetics, we assume that one (dairy) LU represents a combination representative of Swiss dairy cattle holdings in 2014: 48% Swiss Herdbook breed, 38% Swiss Brown, 13% Holstein and 1% Eringer (Swiss milk producers, 2014).

Our hypotheses on explanatory variables are summarized in Table 2.

Table 2: Hypotheses on explanatory variables

Set and	**variable**	**Reference**	**Variable**	**Im-pact**	**Financial success measure**	**Hypothesis**
S	**Size**	Kauffman and Tauer, 1986	LU	+	OLMI	**H1.** Size contributes positively
		Ford and Shonkwiler, 1994	number of calves / heifers	+	net farm income	
		Roesch, 2015	LU	+	income per FWU	
		Roesch, 2015	Area	+	income per FWU	
		Hadrich et al., 2017	LU	+	net farm income	
P	**Milk yield**	Kauffman and Tauer, 1986	milk yield	+	OLMI	**H2**. Milk yield contributes positively
		Ford and Shonkwiler, 1994	milk sold	+	net farm income	
		Vandehaar, 1997	milk yield	+	Profitability	
		Winsten et al., 2000	milk yield per cow	+	Profitability	
		Gloy et al., 2002	milk yield	+	return on assets	
	Purchased feed	Kauffman and Tauer, 1986	Purchased feed per cow	-	OLMI	**H3**. Purcha-sed feed contributes negatively
	Organic produc-tion	Khanal and Mishra, 2016	organic production	-	net cash farm income	Contradictory results – no hypothesis
		Hadrich et al., 2017	organic production	+	net farm income	
D	**Diversifi-cation**	Ford and Shonkwiler, 1994	number of calves / heifers	+	net farm income	**H4**. Diversifica-tion contributes negatively
		Mishra and Morehart, 2001	diversification	-	OLMI	
		Roesch, 2015	area of maize / grassland	-	income per FWU	
		Khanal and Mishra, 2016	direct sales	-	net cash farm income	

further education after apprenticeship and university-level studies. The two lowest and highest levels are aggregated for the three-level assessment.

O	**Full-time farming**	Khanal and Mishra, 2016	non-farm income	-	net cash farm income	**H5**. Full-time farming contributes positively
	Wages paid	Roesch, 2015	number of workers	-	income per FWU	**H6**. Wages paid contribute negatively
	Capitaliza-tion	Mishra and Morehart, 2001	value of machinery and equipment / value of production	-	OLMI	**H7.** Capitalization contributes negatively
E	**Education**	Mishra and Morehart, 2001	level of education	+	OLMI	**H8**. No or low education contributes negatively, high education positively
		El Osta, 2011	high school < college started < college finished	+	farm income	
		Khanal and Mishra, 2016	education	+	net cash farm income	
		Hadrich et al., 2017	college education	+	net farm income	
		Hadrich et al., 2017	no education	-	net farm income	

Choice of panel-data model

Since for all our explanatory variables and income per FWU, the cross-sectional variance is greater than the temporal one (cf. Table A.1 in the Appendix), a random-effects model is preferred. This model additionally allows for a straightforward inclusion of time-invariant explanatory variables. In addition, it is more efficient than its fixed-effects counterpart, i.e. the confidence intervals of its coefficients are narrower.

We use four methods to verify appropriateness of a random-effects model.

First, we use a Hausman test to assess whether the coefficients of a random- and a fixed-effects model are close enough, given their variance, to allow for a random-effects model (cf. Baltagi et al., 2003[12]).

We then apply a Hausman-Taylor model. We first test for endogeneity[13] by assessing the correlations between regressors and the error term of the random-effects model and their significance. Subsequently, coefficients for exogeneous time-varying and time-invariant and, in our case, endogeneous time-varying variables are estimated by the Hausman-Taylor model

[12] "If this standard Hausman test rejects the null hypothesis that the conditional mean of the disturbances given the regressors is zero, the applied researcher reports the FE estimator. Otherwise, the researcher reports the RE estimator." (Baltagi et al., 2003)

[13] Gloy et al. (2002) argue that size should be considered an endogenous variable as it is unclear if success influences size or vice versa or, generally, which direction of influence would prevail, as both could be present. For the Hausman-Taylor model, endogeneity is addressed systematically.

(Baltagi et al., 2003; Hausman and Taylor, 1981). Endogeneous variables are treated as instrumental variables estimated based on the means of the strictly exogeneous variables (cf. Baltagi, 2013). The Hausman-Taylor estimator being consistent (cf. Baltagi and Bresson, 2012, p. 4), we can assess if the random-effects model is consistent with, yet more efficient than, the Hausman-Taylor model by means of a Hausman test.

Next, we apply a correlated random-effects model (Mundlak, 1987). Here, time averages of regressors are added to a random-effects model to assess correlations between the individual effects and regressors directly. If the coefficients of the time averages can be shown to jointly equal zero, there are no correlations between regressors and individual effects, hence no endogeneity: as a result, the random-effects model applies.

We finally compute a FEVD model[14] which estimates time-invariant variables differently from time-varying ones without explicitly considering endogeneity: the coefficients of the latter variables are identical to the ones obtained by the fixed-effects estimator. As the FEVD estimator is consistent (cf. Greene, 2011, p.1), we can again assess by a Hausman test whether the random-effects model is consistent with and more efficient than the FEVD model.

Applicability of a pooled OLS model is tested by a Breusch-Pagan Lagrange multiplier test (Breusch and Pagan, 1980).

Variable selection

The process of selecting variables for the model depends on the set the variable belongs to. We use a modified version of both forward and backward selection criteria which fit our purpose and are specified below. For a general discussion of backward and forward selection using different criteria, see chapter 4 of Harrell (2001).

For sets **S** and **R,** all variables are initially included in the model. Subsequently, a variable is excluded if two conditions are met: firstly, its absence does not decrease the explanatory

[14] The FEVD model is criticized by Greene (2011) for its application to “regressors which slowly vary in time”. We will only apply it to strictly time-invariant regressors.

power (adjusted R^2) of the model and, secondly, its absence does not jeopardize the random-effects model. This represents a version of backward elimination.

Variables of the remaining sets (**P**, **D**, **O** and **E**) are added to the model if its explanatory power increases, the variable yields a significant contribution (assessed by a t-test) and the applicability of a random-effects model is maintained. This is a version of forward selection.

The results presented in Section 3 include a minimum of explanatory variables according to the selection outlined above.

Panel quantile regression and presentation of its coefficients

QR was introduced by Wagner (1959), then taken up by Barrodale and Roberts (1978), Bassett and Koenker (1978), and Koenker and Bassett (1978).

Algorithms for QR minimize a loss function $F(\tau; y(i), x_j(i); \beta)$ depending on the quantile τ of the distribution, or as an equation[15]:

$$\min_{\beta \in \mathbb{R}^p} F(\beta): F(\beta) = \sum_{i \in (i: y_i \geq x_i^T \beta)}^{N} \tau \left| y_i - x_i^T \beta \right| + \sum_{i \in (i: y_i < x_i^T \beta)}^{N} (1-\tau) \left| y_i - x_i^T \beta \right| .$$

N denotes the number of observations, p the number of regressors. Algorithms for QR are implemented in different ways, as the optimization problem does not have a straightforward analytic solution.

QR was first extended to the fixed-effects panel-data case (**QR-FE**) by Koenker (2004). Koenker treats individual-specific, fixed, effects as shifts common to all quantiles. Lamarche (2010) and Canay (2011) propose estimators involving the same quantile-independence of individual-specific effects. Extension to QR-FE proved difficult: The fixed-effects transformation involves differencing, which is commutative[16] with taking the expected value used in the conventional (mean) panel-data model. But the expected value does not occur for QR, where it is replaced by an operation which is not commutative with differencing.

[15] The equation does not directly translate to panel data, but we get an indication for pooled panel data if we replace the index i by a pair of indices (i,t).

[16] interchangeable as a mathematical operation

Hence, consistent estimators of QR-FE have to meet additional conditions. Kato et al. (2012) formulate sufficiency conditions for QR-FE relying on large-T asymptotics[17] and the absence of time-invariant regressors. Abrevaya and Dahl (2008) propose an FE-QR estimator using a correlated random-effects model, estimating fixed-effects as a linear function of regressors and a disturbance. Arellano and Bonhomme (2015) construct QR-FE estimators for short-time panels. Galvao (2008) proposes a QR-FE estimator where individual-specific effects vary over quantiles.

Geraci and Bottai (2007) propose a QR estimator for random-effects models (**QR-RE**) using an asymmetric Laplace density. Kim and Yang (2011) construct a QR-RE estimator based on a semiparametric method using empirical likelihoods. Galvao and Poiriers (2017) propose a QR-RE estimator complemented by a set of tests for its applicability versus a model using time-averages of time-varying regressors. They point out the convenience of QR-RE, as it allows for a small time dimension of the panel and the presence of time-invariant regressors.

We choose the QR-RE estimator by Geraci and Bottai (2014), thus linking our previously motivated random-effects model to a corresponding QR-RE model.

To employ QR, we rely on a number of choices: We use deciles of the income distribution as our data set is large and we aim for a reasonable resolution of results (as opposed to e.g. quartiles with too little or centiles with too much detail) and a smooth path of resulting coefficients along the farms' income distribution.

We also have to decide how to present the QR coefficients: Based on deciles and a set of *p* regressors, *(10-1) * p* QR coefficients result. For a structured overview, we show one overall coefficient for all variables where the minimum and the maximum coefficient differ by less than 1 percent[18] over quantiles, a series of coefficients otherwise. This criterion does not

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[17] i.e. the time dimension of the panel has to be large

[18] As a formula: $2 * (\max_\tau (\beta_{j,\tau}) - \min_\tau (\beta_{j,\tau})) / | \max_\tau (\beta_{j,\tau}) + \min_\tau (\beta_{j,\tau}) | > 1\%$ for regressor j.

imply statistical difference of minimum and maximum coefficients which will be assessed by a Wald-type test (cf. Koenker and Bassett, 1982).

RESULTS

Table 3 shows the results for the random-effects model of income per FWU. **Bold-faced coefficients** denote significance at a less than 0.1% probability value (**p-value**), a high statistical significance, whereas *coefficients in italics* denote a p-value of greater than 10%, a low statistical significance. All other p-values lie between 0.1% and 10%. Our random-effects model explains approximately two fifths of the variance (R^2 = 41%). The overall significance of the model is assessed by a Wald test to be very high (p-value < 0.001).

Admissibility of the random-effects model is shown by the Hausman test with a p-value of 21.9%, application of the Hausman-Taylor model with subsequent Hausman test with a p-value > 99%, and application of the Mundlak correlated random-effects model, where the hypothesis of a coefficient of the time-average regressors different from zero is rejected with a p-value of 52.45%. The FEVD model is consistent with the random-effects model, the latter still being more efficient (p-value > 99%). The statistics of the Breusch-Pagan test with a p-value less than 0.1% rules out a pooled-OLS model.

Table 3: Results of the random-effects model for the annual income per FWU (CHF/FWU)

Explanatory variable	Unit	Coefficient	Standard error	p-value
Unit price of milk	CHF/kg	**31,176**	3,538	<0.001
Owned farmland	ha	129	45	0.004
Natural grassland	ha	**488**	66	<0.001
Artificial grassland	ha	**732**	116	<0.001
Stocking density	LU/ha	3'537	1'055	0.001
Milk yield	kg/LU/a	**2.66**	0.35	<0.001
Organic production	dummy	3,450	1'572	0.028
Input of concentrate feed per dairy cow	kg/LU/a	**-14.2**	1.47	<0.001
Overall diversification	HHI	**8'205**	1'633	<0.001
Agriculture-related diversification	HHI	*-599*	870	0.491
Crop-related diversification	HHI	3,716	1,896	0.050
Share of farm to total income	-	**52'205**	1'491	<0.001
Share of non-FWU	%	**246**	24	<0.001
Farm manager with no finished agricultural apprenticeship	dummy	*-1,913*	2'250	0.395

Farm manager with studies at university level	dummy	*6,188*	4'036	0.125
Farm manager with high educational level outside agricultural sector	dummy	*5,184*	6'162	0.400
Farm manager's partner with low educational level in housekeeping	dummy	*798*	1,111	0.473
Farm manager's partner with low educational level outside agricultural sector	dummy	-4,218	1,185	<0.001
Size of farm manager's household	consumption units	*302*	325	0.354
Capitalization	-	**-20,393**	4,440	<0.001
CH01 - South-Western	dummy	*-138*	5'725	0.981
CH02 - Mittelland	dummy	*4'208*	4'618	0.362
CH03 – North-Western	dummy	*4'816*	5'546	0.385
CH05 - Eastern	dummy	9'591	4'692	0.041
CH06 - Central	dummy	9'674	4'675	0.039
Is mountain canton	dummy	-5'531	1'760	0.002
Constant	-	-39'881	6'753	<0.001

$R^2_{overall}$ = 41.03%; Hausman: p-value = 21.94%; Hausman-Taylor model: p-value > 99%; Mundlak: p-value = 52.45%; FEVD: p-value > 99%; Breusch-Pagan test: p-value = 0%

Milk yield has a strongly significantly positive influence. One additional ton of milk per LU and year increases income by CHF 2660, i.e. by one tenth. Milk price, area of grassland, overall diversification, share of farm to total income and share of non-FWU are additional highly significant proponents of financial success. Other positive determinants are owned farmland, stocking density, organic production and diversification within cropping. Regions with additional positive income are Eastern and Central Switzerland[19].

Capitalization and input of concentrate feed contribute highly negatively to a farm's financial performance. Other significantly negative contributors are a low education of the farm manager's partner outside agriculture and location of the farm in a mountain canton.

We now assess impact after an increase in a variable by one additional unit, one standard deviation or ten percent of its mean value. We only consider statistically significant variables.

For an increase by one additional unit, dummy variables realize the highest impact (since the additional unit is the presence of a certain property, e.g. organic production). The strongest positive contributors are the farm's location in Central (9.7 kCHF or 25.7%) or Eastern Switzerland (9.6 kCHF or 25.5%), a mountain canton is least favorable (-5.5 kCHF or -14.7%). A low education of the farm manager's partner outside agriculture results in an

[19] compared to the canton of Zürich as the base case

income reduction of -4.2 kCHF or -11.2%. Leaving aside dummy variables, stocking density (3.5 kCHF or 9.4%) and share of farm to total income (0.5 kCHF or 1.4%) show the strongest positive impact, capitalization the most significantly negative one (-0.2 kCHF or -0.5%).

After a change by one standard deviation, factors contributing most positively are share of farm to total income (14.8 kCHF or 39.3%), area of natural grassland (5.1 kCHF or 13.6%) and share of non-FWU (5.1 kCHF or 13.5%). Factors contributing most negatively are concentrate input (-5.0 kCHF or -13.2%) and capitalization (-2.3 kCHF or -6.0%).

For a ten percent increase, variables contributing most positively are share of farm to total income (3.7 kCHF or 9.7%), milk price (1.9 kCHF or 4.9%) and milk yield (1.7 kCHF or 4.5%), whereas the most negative contributors are capitalization (-1.3 kCHF or -3.5%) and concentrate input (-0.8 kCHF or -2.2%).

All contributions are considered ceteris paribus.

Table 4: Results of the quantile regression for the annual income per FWU (CHF/FWU)

Variable	Coefficients for quantiles								
	10	20	30	40	50	60	70	80	90
Unit price of milk	**36,651**								
Owned farmland	*116*	*82*	*117*	121	122	122	122	123	127
Natural grassland	**561**	**537**	**562**	**565**	**566**	**566**	**566**	**567**	**571**
Artificial grassland	**855.3**	**849.0**	**855.4**	**856.2**	**856.4**	**856.4**	**856.5**	**856.7**	**857.8**
Stocking density	4,842								
Milk yield	-1.15	*0.36*	0.80	**1.64**	**2.46**	**3.37**	**4.38**	**5.40**	**7.21**
Organic production	**3'075**								
Input of concentrate feed per dairy cow	**-16.1**	**-14.7**	**-13.0**	**-14.0**	**-14.8**	**-15.9**	**-17.0**	**-17.0**	**-16.0**
Overall diversification	**9,809**								
Agriculture-related diversification	*-879*								
Plant-related diversification	*3,500*								
Share of farm to total income	**48,987**								
Share of non-FWU	183	125	190	**198**	**199**	**199**	**200**	**202**	**217**
Farm manager with no finished agricultural apprenticeship	*-918*								
Farm manager with agricultural education at university level	*8,031*								
Farm manager with high educational level outside agricultural sector	*-83*								
Farm manager's partner with low educational level in housekeeping	*-429*								
Farm manager's partner with low educational level outside agricultural sector	**-4,423**								
Size of farm manager's household	*190*								
Capitalization	**-26,606**								

CH01 - South-Western	*207*
CH02 – Mittelland	*3,427*
CH03 – North-Western	*4,187*
CH05 – Eastern	9,302
CH06 – Central	8,956
Is mountain canton	**-5,617**
Constant	**-38,226**

Average pseudo-R^2 = 74.5 %

QR coefficients of six variables differ by more than one percent and are represented as a series of coefficients in Table 4: owned farmland, natural and artificial grassland, share of non-FWUs, concentrate input and milk yield. Milk yield is the only variable whose coefficients change sign for the least and most successful farms. Hence, this variable shows the most diverse results over the range of financial performance. A Wald test for statistical difference between minimum and maximum coefficients among quantiles results in statistical difference for milk yield, where the difference between the 1st and the 9th decile yields a p-value < 0.001, and for concentrate input, where the difference between the 3nd and the 7th decile yields a p-value of 2.5%.

While coefficients of types of farmland vary by less than 10 percent, coefficients of the other variables differ by at least 20 percent. Milk yield contributes strongly to financial success for higher deciles, whereas its impact is significantly negative for the lowest decile. Concentrate input reduces income for all deciles, to a varying degree, especially around the lower end of the income distribution. Share of non-FWU shows a positive result for all deciles.

For the two variables with statistically different coefficients, milk yield and concentrate input, we determine the range of contribution to the mean income per FWU in absolute and relative terms, if increasing the (mean decile) value of the respective variable by 10%. For milk yield, the absolute (relative) contribution ranges from -0.7 kCHF (-21.1%) for the lowest-performing decile of the income distribution to 4.9 kCHF (+5.4%) for the best-performing one[20]. For concentrate input, absolute (relative) contributions range from -1.1 kCHF (-32.3%) for the lowest-performing decile to -0.9 kCHF (-1%) for the best-performing one.

DISCUSSION

For all explanatory variables except milk yield, results will be discussed in the context of our hypotheses of Section 2, attempting to explain contradictions. Results for milk yield are clearly more detailed than in existing literature.

The application of the two models can be seen as a sort of sensitivity analysis. Whereas the random-effects model explains the mean value of income per FWU, QR allows us to analyze points of the income distribution, with the fifth decile representing the median.

Besides the variables with quantile-specific results, the remaining coefficients are similar in terms of significance and value between the random-effects model and QR. All coefficients which are statistically significant for QR are so for the random-effects model. All coefficients of the random-effects model are in the 95% confidence interval of the median QR. All median QR coefficients except the one of the ratio of farm to total income are in the 95% confidence interval of the respective coefficients of the random-effects model[21].

To compare with literature, we distinguish three groups of coefficients.

The first group comprises variables with one single coefficient in both models (milk price; stocking density; overall diversification; the farm being a full-time operation; organic agriculture; capitalization). Here, a comparison to the results obtained in literature is straightforward. The contribution of organic agriculture is in line with Hadrich et al. (2017), who performed an analysis closer to ours by focusing on dairy farming and not on organic farming in general (as in Khanal and Mishra, 2016). Diversification aspects strengthen

[20] Here and for all following discussions in this section, we match the coefficient of the i^{th} decile to the mean values of the $(i\text{-}1)^{st}$ to the i^{th} decile which are noted under decile *i* in Table 1.

[21] There are still small differences: Focusing on quasi-constant coefficients significant in both models, four coefficients are greater for QR than for the random-effects model (milk price; stocking density; overall diversification; location in the first macro-region), ten coefficients are smaller (organic production; diversification in cropping; share of farm to total income; capitalization; low education of the farm management's partner outside agriculture; location in the second, third, fifth or sixth macro-region or in a mountain canton).

economic success in our model and contradict the results of Mishra and Morehart (2001) and of Roesch (2015), if for the latter we take larger areas of crop production as a sign of stronger diversification. Mishra and Morehart (2001) use a diversification index most similar to ours, while their sample of US dairy farms is located at 57% in the, rather flat, Midwest region and 27% in the Northeastern US and hence shows a higher weight on valley-like regions for which our model shows a negative contribution of overall diversification[22]. Capitalization is confirmed to have a negative, highly significant, influence on a dairy farm's economic performance, whereas the negative impact in the study of Mishra and Morehart (2001) was statistically insignificant.

The second group focusses on variables with a set of coefficients for QR, and a single one in the random-effects model (owned farmland; natural and artificial grassland; share of non-FWU on farm; input of concentrate feed per cow). The positive contribution of size-related aspects is consistent throughout literature (Kauffman and Tauer, 1986; Ford and Shonkwiler, 1994; Winsten et al., 2000; Mishra and Morehart, 2001; Gloy et al., 2002; Roesch, 2015; Hadrich et al., 2017). The positive contribution for the share of non-FWU in our model contradicts the results of Kauffman and Tauer (1986), Gloy et al. (2002), or Roesch (2015). However, the variables used by these authors differ slightly from ours as they chose wages paid or the absolute number of hired workforce. Our results on the negative contribution of concentrate input match the results of Kauffman and Tauer (1986).

The third group consists of variables where the random-effects model results in a significantly positive coefficient, whereas QR results in a set of coefficients with significant positive and negative contributions depending on the quantile. Only milk yield belongs to this group. The positive impact of milk yield in our random-effects model confirms literature (Kauffman and Tauer, 1986; Ford and Shonkwiler, 1994; Vandehaar, 1997; Winsten et al., 2000; Gloy et al.,

[22] If we restricted our model to the valley region, diversification aspects would turn out to be negative (results not reported).

2002), whereas different signs of coefficients for different quantiles have not been reported so far.

We also compare our results to models explaining the costs of dairy production. Cost determinants might be expected to be opposite to the ones of income per FWU, but, income being revenue less costs, results could be more complex.

Hoop et al. (2015) analyze the full cost of producing one kilogram of milk on Swiss dairy farms. The authors determine milk yield and size - in LU and area - to reduce costs; silage-free production, assets including machinery, buildings and equipment, superior conditions of animal welfare, age of the farmer, and share of hired workforce increase costs. In terms of milk yield and size of the enterprise, decreased costs translate into higher income, in our analysis, whereas the gain in revenues by non-FWU outweighs the increased cost.

Referring to Table 2, we reject hypotheses H4 and H6, keeping in mind the difference in choice of variables. We confirm H2 for the random-effects model, whereas QR yields a more detailed picture. H1, H3, H5, H7 and H8 are confirmed for both our models.

With respect to literature using QR, we are interested in the share of coefficients that vary among quantiles. In our model, about one fourth of the variables has varying coefficients. El Osta's (2011) results are similar in that a quarter of the coefficients of explanatory variables show an increasing or decreasing tendency over quantiles. The remaining variables show statistically insignificant results for most quantiles. For the QR conducted by Khanal and Mishra (2016), seven out of seventeen coefficients decline or increase over the income distribution, the remaining ones not showing any particular trend or remaining statistically insignificant. A sixth of the coefficients in the QR of Hadrich et al. (2017) show a linear tendency; the rest stays statistically insignificant or without any particular tendency. Hence, the share of coefficients displaying a linear tendency along the distribution is similar to ours, while the coefficients that show no such tendency do not stay constant for all quantiles, but fluctuate somewhat more than in our model.

We also assess confirmation of our QR results by literature. Hadrich et al. (2017) complement their mean regression of net wealth and income of US dairy farms by QR. They conclude that, for net worth, size of the operation has a positive and increasing impact, as do college education and age brackets of the farmer from 35 years onwards. For net farm income, size and organic production show a higher impact for more successful farms. The size effect agrees with our results; the impact of organic farming is qualitatively identical to our analysis. A number of QR coefficients in the study of Hadrich et al. (2017) vary per quantile without showing any directional trend, corresponding to the case of our twenty quantile-independent variables, but the relative difference in size between the coefficients per quantile is much smaller in our case.

CONCLUSIONS

The paper analyses determinants of income per FWU for Swiss dairy farms based on FADN data by means of two regressions: a random-effects model and a QR based on deciles. Milk yield and concentrate input play a significant role in both models.

Although the random-effects model shows a significant positive effect of milk yield on income, QR reveals a much more detailed picture. For six out of twenty-six explanatory variables, QR reveals a linear tendency in coefficients across the deciles instead of a single coefficient as for the random-effects model. The impact of milk yield on income is increasing with income. With additional CHF 7’200 per additional ton of milk yield per LU, i.e. 16% of increase compared to the mean income of dairy farms, the best-performing decile benefits strongly, suggesting a thorough understanding of production technology and economic performance on these farms.

For the least successful decile of dairy farms, the contribution of an additional kilogram of milk is negative, whereas for the two subsequent deciles there is no statistical impact of a higher milk yield on income. More generally, the analysis with two regression models reveals that the data includes a kind of heterogeneity which cannot be addressed by a regression focusing on the mean value. Accordingly, the results confirm the contribution of QR in terms of additional knowledge gained, in our case for milk yield as a key factor of milk production systems.

For consulting or extension services provided to dairy farmers, our results imply that the individual situation needs to be considered. A general advice such as additional milk yield being beneficial is not indicated.

To test whether the found effect is specific to Switzerland, a similar analysis in other countries would be interesting.

In addition, it remains to be understood how a path leading from a less successful to a more successful dairy farm could be described, and what role further nutritional factors as well as genetics could play.

ACKNOWLEDGMENTS

The authors are grateful to the FADN team of Agroscope for providing the data and to Nadja El-Benni and Swetlana Renner for comments.

APPENDIX

Construction of the diversification index

The Hirshman-Herfindahl index H_0 (Hirshman, 1964) is given by

$$H_0 = \sum_{i=1}^{N} (\frac{s_i}{s})^2 \in [\frac{1}{N}; 1] \text{ with } = \sum_{i=1}^{N} s_i \ . \qquad (1)$$

Quantities s_i are variables whose concentration should be assessed: here, they are taken as revenues from a diverse set of farming operations, e.g. crop production, animal production except dairying, or agriculture-related activities. As the HHI assesses concentration, we invert it to measure diversification:

$$H_i = \frac{1}{H_0} \in [1; N] \qquad (2)$$

Subsequently, the inverted index is normalized:

$$H_i^n = \frac{(H_i - N)}{(1 - N)} \in [0; 1]. \qquad (3)$$

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Distributional values and mean decile values

Variable	Unit	Mean	Decile										Variance			Set
			1	2	3	4	5	6	7	8	9	10	o	b	w	
Annual income per FWU	**kCHF/ FWU/a**	**42.8**	-7.7	14.4	22.7	29.6	36.0	42.8	50.0	59.6	73.6	107.6	33.5	31.2	15.1	-
Number of livestock	**LU**	**30.3**	25.1	22.6	24.8	26.1	28.3	30.3	31.5	33.0	36.8	44.8	15.4	15.7	2.1	**S**
Owned farmland	**ha**	**16.8**	12.6	13.7	14.5	15.2	16.3	17.5	17.8	18.1	19.5	23.3	13.7	13.5	1.5	**S**
Utilized agricultural area	**ha**	**23.1**	18.3	17.9	19.0	20.7	22.1	23.4	24.2	25.1	27.6	32.3	11.2	11.2	1.2	**S**
Artificial grassland	**ha**	**2.7**	1.8	1.6	2.2	2.2	2.4	2.6	2.5	2.7	3.6	5.1	4.9	5.1	1.1	**S**
Natural grassland	**ha**	**18.9**	15.5	15.6	15.8	17.3	18.3	19.3	20.2	20.5	21.8	24.4	10.5	10.5	1.5	**S**
Stocking density	**LU/ha**	**1.32**	1.35	1.25	1.32	1.27	1.28	1.29	1.33	1.34	1.37	1.38	0.49	0.57	0.11	**S**
Milk price	**Rp/kg**	**59.4**	55.6	55.2	57.3	58.1	59.4	59.6	60.3	60.4	62.6	65.3	13	12	5	**P**
Milk yield	**t/LU/a**	**6.41**	6.19	6.02	6.22	6.21	6.37	6.46	6.46	6.65	6.64	6.91	1.31	1.25	5.2	**P**
Organic production	dummy	**0.16**	0.12	0.11	0.17	0.18	0.18	0.17	0.19	0.17	0.18	0.18	0.37	0.36	0.03	**P**
Concentrate feed per dairy cow	**CHF/LU/a**	**802**	969	819	796	786	810	786	780	783	724	766	480	479	160	**P**
Overall diversification	-	**0.32**	0.27	0.29	0.31	0.34	0.33	0.32	0.33	0.32	0.33	0.35	0.25	0.23	0.11	**D**
Agriculture-related diversification	-	**0.26**	0.31	0.31	0.28	0.26	0.26	0.25	0.21	0.20	0.26	0.22	0.41	0.37	0.22	**D**
Plant-related diversification	-	**0.07**	0.08	0.09	0.06	0.06	0.06	0.06	0.07	0.07	0.07	0.08	0.17	0.14	0.10	**D**
Share of farm to total income	**%**	**70.0**	20.2	57.1	67.0	72.4	76.4	78.6	80.0	81.9	84.0	84.3	0.28	0.27	0.12	**O**
Share of non-family work units	**%**	**18.2**	21.7	12.7	11.8	12.9	14.3	15.1	17.2	19.6	22.6	33.7	20.6	20.7	5.6	**O**
Size of farm manager’s household	**SCU**	**3.52**	3.50	3.26	3.54	3.53	3.65	3.68	3.56	3.56	3.55	3.41	1.50	1.48	0.37	**O**
Capitalization index	-	**0.65**	0.66	0.67	0.66	0.66	0.64	0.65	0.64	0.63	0.64	0.62	0.11	0.11	0.04	**O**
Farm manager with no finished agricultural (ag.) apprenticeship	dummy	**0.06**	0.11	0.07	0.06	0.05	0.07	0.05	0.04	0.06	0.05	0.03	0.07	0.07	0.02	**E**
Farm manager with ag. studies at university level	dummy	**0.02**	0.01	0.02	0.01	0.01	0.01	0.01	0.01	0.01	0.03	0.06	0.13	0.14	0.01	**E**
Farm manager with high educational level outside ag. sector	dummy	**0.01**	0.01	0.01	0.01	0.00	0.01	0.01	0.01	0.01	0.01	0.01	0.09	0.09	-	**E**
Farm manager's partner with low educational level in housekeeping	dummy	**0.35**	0.38	0.33	0.33	0.35	0.34	0.35	0.38	0.34	0.31	0.34	0.48	0.47	0.09	**E**
Farm manager's partner with high educational level outside ag. sector	dummy	**0.04**	0.03	0.04	0.03	0.03	0.04	0.02	0.04	0.03	0.02	0.08	0.19	0.18	0.03	**E**
CH01: South-Western	dummy	**0.03**	0.04	0.06	0.04	0.04	0.04	0.03	0.02	0.03	0.02	0.02	0.18	0.18	-	**R**
CH02: Mittelland	dummy	**0.42**	0.36	0.41	0.43	0.44	0.43	0.46	0.43	0.39	0.39	0.45	0.49	0.49	-	**R**
CH03: North-Western	dummy	**0.03**	0.04	0.01	0.02	0.02	0.02	0.03	0.04	0.04	0.03	0.04	0.16	0.17	-	**R**
CH04: Zürich	dummy	**0.01**	0.00	0.01	0.01	0.03	0.02	0.02	0.01	0.02	0.02	0.00	0.12	0.12	-	**R**
CH05: Eastern	dummy	**0.23**	0.21	0.19	0.19	0.20	0.24	0.25	0.29	0.27	0.26	0.25	0.42	0.41	-	**R**
CH06: Central	dummy	**0.27**	0.35	0.33	0.31	0.28	0.26	0.21	0.22	0.25	0.28	0.23	0.45	0.45	-	**R**
Is mountain canton	dummy	**0.15**	0.27	0.24	0.22	0.17	0.17	0.10	0.13	0.09	0.08	0.06	0.36	0.37	-	**R**

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