Factors affecting the situation of economically weak farms in Switzerland

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Abstract

Data from the Farm Accountancy Data Network (FADN) over the period 2005 to 2010 were used to determine the factors that contribute to the financial performance of economically weak farms in Switzerland. The study analyses the economic performance of all farms represented in the 2005-2010 sample period found in terms of work income per family labour unit. To address this issue, the farms were split into two groups: the successful Group A, comprising farms with incomes above CHF 18,300, and the unsuccessful Group B, in which farms remain below this threshold. The differences between the farms in Group A and B were analysed using a panel data logit models. The study found ample evidence that full-time farms tend to be more successful in belonging to the successful group A than farms run only on a part-time basis. The analysis reveals that farms with specialist crops (fruit, vegetables, vines) and finishing farms (pigs and poultry) more frequently belong to the successful Group A than those geared to a different type of production (e.g. cattle rearing or dairy farming).

Keywords: *farm income, farm success, economic performance, logistic regression, panel models*
JEL Classification: *Q12*

Introduction

The Agroscope Reckenholz Tänikon ART Research Station has been collecting accountancy data from farms and analysing the economic situation of Swiss farmers since the 1970s. The results are published in standard works (e.g. Dux and Schmid, 2010), the farming press, ART Reports, and scientific publications. Two press releases on the economic situation in Swiss agriculture are also issued annually. The assessments are based on the accounts of a (non-random) sample of around 3,500 farms, with the composition changing over the course of time. Weighted extrapolation can be used to apply the results to the Swiss agricultural sector with its approximately 50,000 farms.

In 2009, Swiss farms earned an agricultural income of around CHF 60,000 per farm. The average work income (WI) per annual work unit (AWU) was around CHF 41,200. The work income per AWU is the generated value-added that remains available per AWU after all other production factors (equity included) have been remunerated. The differences in WI/AWU between the three regions (lowland, hill, and mountain) are considerable. Over the three years 2007-2009, the median of the WI/AWU in the lowland region was on average approximately CHF 48,200, whilst the figure was CHF 34,770 for the hill region and just CHF 25,012 for the mountain region. These figures are considerably below the comparison incomes calculated by the Earnings Structure Survey of the Swiss Federal Office of Statistics. The comparison wages are defined as

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the median of the gross wage for the secondary and tertiary sectors. Thus, WI/AWU stands at 67% of the comparison wage in the lowland region, 53% in the hill region, and just 41% of the said wage in the mountain region.

The aim of this study is to investigate the success of farms with a low WI/AWU in improving their economic performance. Because – as outlined above – low income levels are the reality for many farming families, it is of crucial importance to learn more about the structure of farms with very low income levels.

The farms analysed will be those that were in the FADN sample in the analyzed period 2005-2010. Data panel logit regression analysis (see e.g. Hosmer and Lemeshow, 2000; Cohen et al., 2003; Backhaus et al., 2006; Greene, 2011) is used to identify factors affecting the probability of staying above the first quartile with respect to its income situation.

In this paper, the data is described in Section 2, followed by the methodology part in Section 3. The results are discussed in Section 4, and we conclude with a short summary in Section 5.

Data

This paper is based on the bookkeeping data collected at the Swiss Farm Accountancy Data Network between 2005 and 2010. In 2005, the Swiss Farm Accountancy Data Network sample comprised 3135 farms. The corresponding sample sizes for the five following years, 2006-2010, were as follows: 3271 (2006), 3328 (2007), 3376 (2008), 3372 (2009) and 3202 (2010). The composition of the sample changes from year to year, with around one-fifth of all farms leaving the sample annually, while roughly the same number of new farms were included in the sample. The data collected were thoroughly checked for plausibility in several hundred tests, and should therefore meet high quality standards. Nevertheless, detailed checking of the data revealed some serious problems such as negative gross performance or farm managers aged seven years. This outliers were ignored in this study, leading to a total of 16367 observations or 4457 farms. So, in average, a single farm stays approximately 3.7 years in the sample.

The Analytical Framework

Indicator for farm success

Farm financial success can be defined in different ways. Although the literature reveals that there is no consensus on one specific measure (Foreman and Livezey, 2003), most researchers use a measure of net income (Tvedt et al., 1989; Ford and Shonkwiler, 1994; McBride and Johnson, 2004).

Here, we define farm profitability on the basis of WI/AWU, that is, the value-added per AWU remaining available after the remuneration of all other production factors. This definition of profitability is - despite of his simplicity – very powerful as WI is the “bottom line” of the farm business. Over the long term, WI (together with the non-farm income) is the amount available for discretionary use by the family and for business development. Due to its outstanding meaning, it is thus not surprising that the net farm income, defined as the sum of WI and the interests for loan capital, is used in the definition of various profitability indices such as the return on assets (ROA) or profit margin.

Group allocation

In this investigation, farms will be considered successful if their work income is above CHF 18,300 which corresponds to the (weighted) 25th percentile of the pooled accountancy data from 2005-2010. Based on this definition, the sample consists of 13,065 "successful" farm accountancies while 3302 datasets belong to the "unsuccessful" group. The successful farms belong to Group A. Group B comprises the unsuccessful farms, Group affiliation is represented by the target variable Y (response variable) of interest to us, and, as seems natural, is coded with the values Y=0 (Group B) and Y=1 (Group A). The response variable is named *group* in the model specification.

Factors influencing farm success

The present paper focuses primarily on determining the likelihood of a farm remaining in Group A or Group B subject to a number of predictor variables. An important but challenging task for modelling Group A and B using data panel logit regression is to select and define the most meaningful variables and indicators possible, in order to characterise the farm as well as possible in terms of its structure and economic situation. The selection of possible explanatory variables to describe the target variable (Group A or Group B) comprised the following three steps: (i) literature review, (ii) discussion with experts in farm management, and (iii) adoption of suitable indicators to characterise the farm as well as possible.

Numerous studies have analysed factors contributing to (financial) farm success (Haden et al., 1989; Boessen et al., 1990; Plumley et al., 1991; El-Osta and Johnson, 1998; Mishra et al., 1999; Foreman and Livezey, 2003; Makokha et al., 2007; Hassan and Nhemachena, 2008). The literature review provides a basic set of key variables that generally have significant correlations with farm success: farm size, productivity, percentage of leased land (tenure), age of farm manager, level of specialisation and off-farm employment, debt-to-asset ratio, and the ratio of variable expenses to the value of production. Note, however, that the available literature on the success of (economically) small farms is quite limited (e.g. Yeboah et al., 2010). Furthermore, studies often focus on a single farm type such as dairy or crop farms, or do not cover all aspects of farm performance but concentrate, for example, on the adaptation to climate change (Carroll et al., 2009; Hassan and Nhemachena, 2008). Factors chosen for this analysis are those which the literature suggests as impacting on farm success. Since this study does not merely cover a homogeneous group of farms, several additional variables such as region (*reg*) or farm type (*typ*) were added as explanatory variables. The level of specialisation will be estimated in this study by the number of farm branches (i.e. farming activities). Age and education of farm manager are used to represent the operator's experience and risk-taking preferences (Foreman and Livezey, 2003).

The final result of the three-step procedure described above is reproduced in a grouped form in Table 1. The capital for the partial productivity indicator 'capital productivity' is defined as the sum of amortisations, interest on debts, and calculated interest on equity capital and rents, all measured in Swiss francs.

Table 1: Specification of the logistic regression input variables. The italicised abbreviations in brackets are used throughout the text. Each of the characteristic variables was recorded in the start year 2005 unless otherwise indicated. For categorical variables, the meaning of individual steps is given.

Category	Explanatory variable x_j
Location of farm	Region (*reg*) 1: Lowland region 2: Hill region 3: Mountain region
Structure of farm	Utilised agricultural area (*uaa*) in 2005
	Form of employment (*empl*) 1: Full-time (proportion of agric. income to total income >90 %) 2: Over-half-time (proportion of agric. income to total income 50-90%) 3: Part-time (proportion of agric. income to total income < 50 %)
	Proportion of leasehold to total farm area (*fraclh)*
	Proportion of paid labour units (employees) (*fracemp*) Total labour = employees + family labour units
Sociological factors of farm manager	Age (*age*)
	Education (*educ*) 0: No professional training 1: Professional qualification or continuing education (e.g. master's certificate)
Type of farm production	Type of production (*bio*) 2: PEP (Proof of Ecological Performance) 3: Organic farm
	Type of farm (*typ*) 1: Farm type 'Specialist crops' (fruit, vegetables, vines), 'Finishing' (pigs & poultry) or 'Combined finishing'. See Meier (2005) for a precise definition of farm types. 0: Other farm types (Type 11, 21, 22, 23, 31, 51, 52 and 54, see Meier (2005)
	Ratio of gross performance from livestock farming to total gross performance (frac*gpcat*). Gross performance is the total value of products and services produced in the accounting year.
	Number of farm branches (*numbranch*). A farm branch is a sub-segment defined by the type of products produced, e.g. 'Wheat' or 'Milk production'.
Financial situation of farm	Degree of indebtedness = degree of external financing = debt equity ratio (*der*)
	Assets per labour unit (*asslu*)
	Ratio of direct payments to total gross performance (*dpgp*)
Partial Productivity indicators	Labour productivity = $\frac{gross\ performance}{annual\ labour\ unit}$ (*lapr*)
	Capital productivity = $\frac{gross\ performance}{capital}$ (*cappr*)
	Land productivity = $\frac{gross\ performance}{UAA}$ (*landpr*)

The following input variables were subjected to logarithmic transformation (logarithm to the base 10) according to the 'first-aid' transformation: (i) the three productivity indicators *(LaPr, CapPr, LandPr), and (ii)* assets per labour unit (*AssLU*). The positive side-effect of these transformations was a significant reduction in the skewness of the corresponding distributions.

It is evident from the literature that numerous other factors such as good management practices, knowledge and early adoption of new technology, and love of farming impact on farm success (e.g. Hassan and Nhemachena, 2010). In addition, information on the farm manager's decision-making process and the organisation of the farm may affect farm profitability. Note that for this study we exclude these variables as candidates, since all explanatory variables are exclusively retrieved from FADN data.

Panel data logit model

The characteristics of the problem suggest using a panel data logit model in order to profit the best from the longitudinal data and the fact that the study aims at the prediction of the binary target variable *group*. The panel data logit model combines the theory of panel data model and logistic regression. A brief introduction into the model used is provided in the following. More details are given in the literature (e.g. Chaps. 13 & 14 in Wooldridge (2003) for an introduction into panel models, and Chap. 7 in Dobson and Barnett (2008) for an overview on logistic regression).

Logit model

Logistic regression (sometimes also called logit regression), allows one to predict a discrete outcome, such as group membership, from a set of variables that may be continuous, discrete, dichotomous, or a mix of any of these.

The basic statistical model for logistic regression is the logit function g which is defined as

$$g = \mathrm{logit}(\pi) = \log\left(\frac{\pi}{1-\pi}\right) = \alpha + \sum_{j=1}^{m} \beta_j \cdot x_j = \eta \tag{1}$$

with $\pi = P[Y = 1|\underline{x}]$ the probability of the event occurring, Y the binary response variable, P the probability and m the number of predictor variables x_j . The β_j's are the logistic regression coefficients or logit coefficients, η is called the linear predictor. For simplicity reasons we omit the index i (i=1,..., N) for the observation i in Eqs. (1)-(5).

The logit function g is the link function of the logistic regression and assigns the log odds to the probabilities π. The odds θ are defined as follows

$$\theta = odds(Y = 1|\underline{x}) = \frac{P[Y=1]}{P[Y=0]} = \frac{P[Y=1]}{1-P[Y=1]} = \frac{\pi}{1-\pi} = e^{\alpha+\beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_m x_m} = e^{\eta} \tag{2}$$

The odds are thus the ratio between the probability of the event occurring (Y=1) and the event not occurring (Y=0) and can take values between 0 and +∞.

The double ratio (odds ratio) is given by

$$\phi = \frac{odds(y=1|x_k=l+1)}{odds(y=1|x_k=l)} = \frac{e^{\alpha+\beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_k \cdot (l+1) + \ldots + \beta_m x_m}}{e^{\alpha+\beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_k \cdot l + \ldots + \beta_m x_m}} = e^{\beta_k} \tag{3}$$

From Eqs. (2) & (3) it simply follows that the logarithm of the odds (log odds) are computed as

$$\log(\theta) = \log\left(\frac{\pi}{1-\pi}\right) = \alpha + \sum_{j=1}^{m} \beta_j \cdot x_j = \eta \tag{4}$$

From Eq. (2) the probability π that the (binary) target variable Y has the value 1 can be determined as following

$$\pi = \frac{1}{1+e^{\alpha+\beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_m x_m}} = \frac{1}{1+e^{\eta}} \tag{5}$$

Marginal effects are commonly used in practice to quantify the effect of variables on an outcome of interest. The marginal effect of an explanatory variable x_k is the effect of an unit change of this variable on the probability P given that all other predictor variables are constant:

$$\frac{\partial P(Y=1|\underline{x})}{\partial x_k} \xrightarrow{yields\ (\partial x_k=1)} P\left[Y = 1|\underline{x}_{(k)}, x_k = l+1\right] - P\left[Y = 1|\underline{x}_{(k)}, x_k = l\right], \tag{6}$$

where $\underline{x}_{(k)}$ denotes the means of all the other variables in the model. The marginal effect thus measures how much the predicted probability π changes when the predictor variable x_k increases by 1.

For the estimation of the intercept α and the β coefficients we use the maximum likelihood (*ML*) method. *ML* estimates the model parameters so that the probability of obtaining the observed characteristics is maximal. The calculations are carried out iteratively using the Newton-Raphson algorithm (Süli and Mayers, 2003).

The performance of the fitted model can be examined by different criteria. Often the log likelihood ratio or Wald test is used for analyzing the significance of the coefficients (Dobson and Barnett, 2008). Sometimes the log-likelihood function for the fitted model is compared with the log-likelihood function for the minimal model, in which the values π_i, i=1,..., N (number of observations) are all equal.

Further, the performance of the model can also be checked with an analysis of the classification results. Here, the observed values of the binary target variable Y (0 or 1) are compared with the probabilities generated, the separation value being set at a probability of $P[Y=1]=0.5$:

$$\hat{Y}=1, \text{ if } P[Y=1] > 0.5$$
$$\hat{Y}=0, \text{ if } P[Y=1] <= 0.5, \tag{7}$$

where the caret ($\hat{\cdot}$) denotes the estimated value of the response variable Y. With the aid of a contingency table, a conclusion can be reached on the 'hit ratio' (correct allocations), which can be compared with a purely random hit ratio that depends on the frequency of the observed values Y =0 and Y =1.

Panel model

The term "panel" refers to "a group of individuals surveyed repeatedly over time" (Frees 2004). Panel data models are well suited for our purpose as they can be easily applied to unbalanced data such as the FADN data set in which the time periods differs across individuals. For simplicity reasons, the following formulae set is given for linear panel models.

The basic linear panel models used in econometrics can be described through suitable restrictions of the following general model

$$y_{it} = \alpha + \sum_{j=1}^{m} (\beta_{ijt} \cdot x_{ijt}) + v_{it} \, , \tag{8}$$

where i=1,…, N is the observation (farm) index, t=1,…, T is the time index, j=1,..., m is the index for the explanatory variable j, and v_{it} is an error term of mean 0. In order to model the error term v_{it}, this term is often split into two separate components, one of which (u_i) is farm specific and does not change over time while the other (ϵ_{it}) represents random or idiosyncratic disturbances:

$$y_{it} = \alpha + \sum_{j=1}^{m} [(\beta]_{ijt} \cdot x_{ijt}) + u_i + \epsilon_{it} \, . \tag{9}$$

The following three approaches are typically used. This study does not consider the first case but only the two latter ones:

1) OLS: Pooling of all data across i and t. This leads to ordinary least squares (*OLS*). This approach is seriously questioned for this study's purpose due to serial autocorrelation between observations and the ignorance of individual heterogeneity. Regular *OLS* regression does thus not consider heterogeneity across individuals or time.
2) Fixed Effects approach: The individual effects u_i, i=1,..., N are estimated separately. This model treats unobserved differences between individuals as a set of N fixed parameters. This is equivalent with the statement that the unobserved individual effects u_i are allowed to be correlated with the observed explanatory variables x_j.
3) Random effect approach: In this model unobserved differences between individuals are treated as random variables with a specified probability distribution. In a random effects model, the unobserved variables are assumed to be *un*correlated with all the observed variables.

The Hausman specification test compares the fixed versus random effects under the null hypothesis H_0 that the individual effects u_i are uncorrelated with the other regressors in the model (Hausman, 1978). If correlated the null hypothesis H_0 is rejected: a random effect model produces biased estimators, thus violating one of the assumptions. So a fixed effect model is preferred. In other words, if H_0 is rejected, the fixed-effects model should be favoured over the random-effects model.

By replacing the response variable y_{it} in Eq. (9) through the logit function (see Eq. (1)) we come up with the panel data logit model. Note that for the fixed effect estimators, it is necessary to drop from the sample any farm that have y_{it} equal to zero or one for the entire period.

4. Results and Discussion

Main differences between Group A and Group B

First of all, a short descriptive overview of the differences between the successful (Group A) and unsuccessful (Group B) farms is given. Table 2 shows the six-year averages (2005-2010) of groups A and B. The successful (Group A) and unsuccessful (Group B) farms differ considerably from each other in terms of both structure and economic situation. Whereas Group B farms on average farmed an area of 17.8 ha and kept a herd of 24.0 livestock units (LU), the corresponding figures for the successful farms were substantially higher, at 23 ha and 31 LU. The difference in income between the two groups was even more significant. At CHF 17,500, the agricultural income of Group B farms was just one-fourth that of the successful farms (CHF 72,600). Group B farms earned a small work income per family labour unit (CHF 4400), thus receiving almost no remuneration for family labour performed, whilst Group A achieved the distinctly higher value of approx. CHF 50,200. These differences were due *inter alia* to the significantly higher gross performance of farms in Group A, which stood at around CHF 80,000 above the gross performance of the B farms, whilst only just under CHF 24,000 more was disbursed on the cost side (external costs). The income gap of the B farms in the agricultural sector was at least partially closed by a significantly higher income from non-agricultural activity, which is why the total income per consumer unit in the successful group was on average only CHF 8500 above the corresponding figure for the farms in Group B.

Table 2: Key structural and economic figures for Group A (successful farms) and Group B (unsuccessful farms), mean for 2005-2010. Note that the results for Group A and B are unweighted means.

		Group A	Group B
Utilised agricultural area	ha	23.0	17.8
Livestock	LU	31.0	24.0
Gross performance	CHF	271,500	192,300
External cost	CHF	198,900	174,800
Operating income	CHF	101,500	42,500
Agricultural income	CHF	72,600	17,500
Work income per AWU	CHF /AWU	50,200	4,400
Off-farm income	CHF	19,000	32,300
Total income per consumer unit	CHF/CU	22,900	14,400

Estimate of coefficients

The fixed and random effect logit models are fitted with the Stata's *xtlogit* procedure. The two methods (fixed vs. random) were compared using the Hausman specification test. This test results in a highly significant rejection of the null hypothesis H_0, indicating that the fixed-effects model should be favoured over the random-effects model. The likelihood ratio test is virtually zero, indicating that the fitted model is highly statistically significant different from the null model (with all β coefficients set to 0). The collinearity of variables was tested using the variance inflation factor (*VIF*). It provides an index that measures how much the variance (the square of the estimate's standard deviation) of an estimated regression coefficient is increased because of collinearity. Here, all VIF's stay below a value of 6.0, indicating that multicollinearity is unlikely a problem in our model as only values in excess of 20 are suggested as indicative of a problem (Greene, 2011, p. 90).

The regression coefficients from the fixed effect logit model along with their stand errors and confidence intervals are given in Table 3. Out of the 17 predictor variables, 10 have turned out to be significant at the 5% level. For both of the variables *empl* and *reg*, the baseline category is 1.

Note that stepwise regression procedures for reducing the number of covariates were not applied as these methods often lack a clear logical foundation and generally end up with a set of variables that are relatively uncorrelated (Griliches and Intriligator, 1983). Harrell (2001) discovers a number of further critical issues when applying the stepwise regression procedures such as "loosing of valuable predictive information from deleting marginally significant variables". Furthermore, Antonakis and Dietz (2011) stated very recently that "omitted covariates may be jointly significant even if they are not significant individually", concluding that important theoretical control variables should never be dropped from the regression model.

Table 3: Maximum likelihood estimates, standard errors, p-values and 95% confidence intervals for the fitted panel data logit model. Where predictors are represented by dummy regressors, the category coded 'one' is given in brackets. For variables 'empl' and 'reg', the baseline category is 1. Bold numbers indicate that coefficients are statistically significant at the 0.05 level.

	Coef.β	Std.Err.	z	P>|z|	95% confidence Interval	
reg (2)	0.009	0.469	0.02	0.984	-0.909	0.928
reg (3)	-4.076	3.118	-1.31	0.191	-10.187	2.036
uaa	0.078	0.038	2.02	0.043	0.002	0.153
typ	1.346	0.330	4.07	0	1.993	0.698
empl (2)	-1.299	0.181	-7.18	0	-1.654	-0.945
empl (3)	-5.155	0.326	-15.82	0	-5.794	-4.517
educ	0.138	0.856	0.16	0.872	-1.539	1.815
age	-0.10	0.24	0.87	0.410	-0.58	0.39
bio	0.451	0.493	0.92	0.360	-0.515	1.418
fracemp	1.242	0.570	2.18	0.029	0.126	2.359
numbranch	-0.018	0.048	-0.38	0.702	-0.113	0.076
der	-1.782	0.787	-2.26	0.024	-3.323	-0.240
fracgpcat	-2.610	0.950	-2.75	0.006	-4.471	-0.749
lapr	15.799	1.254	12.6	0	13.342	18.257
cappr	3.757	0.763	4.93	0	2.262	5.252
landpr	5.103	1.550	3.29	0.001	2.066	8.141
dpgp	-1.771	1.877	-0.94	0.346	-5.449	1.908
fraclh	-0.299	0.911	-0.33	0.742	-2.084	1.486
asslu	-2.894	0.907	-3.19	0.001	-4.671	-1.116

Results and Discussion

Table 3 provides a summary on the regression coefficients and its statistical significance from fitting the data panel logit model. For both of the variables *empl* and *reg*, the baseline category is 1.

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We start with the discussion of statistically significant coefficients. According to Eq. (4), β_j shows the amount of change in the log odds for a one unit change in the covariate x_j. Unfortenately, log odds do not have a simple interpretation. So, instead of interpreting the sizes of coefficients, we interpret their signs only: Positive coefficients indicate that as x_j increases, the probability of staying in Group A, i.e. $\pi=P(Y=1)$, increases as well. From this we conclude that the probability of being in the successful group A increases with (i) growing agricultural area (*uaa*), (ii) rising proportion of paid labour units (*fracemp*), and (iii) increasing productivity indicators *lapr, cappr* and *landpr* (cf. Table 3). It is evident that higher productivities favours the change into the successful group A. Further, higher proportion of paid labour obviously triggers the agricultural income in a positive way. The farm family is better off paying external employees, e.g. during harvest time, in order to avoid acquisition, repair and maintenance of expensive machinery. The positive scale effect is reflected in the positive value of β_{UAA}: The larger farms the more likely it stays in Group A. This is in line with other studies (e.g., Carroll et al., 2009).

In contrast, π *de*creases for increasing values of the three covariates debt equity ratio *(der),* the ratio of gross performance from livestock to total gross performance *(fracgpcat),* and the assets per labour unit *(asslu*). The latter possibly suggests that investments in machinery and buildings have exceeded the optimal levels due to overmechanization. This gives some evidence that, farming as a capital-intensive business, should rather hire labour than invest in (often expensive) machinery. The higher the debt equity ratio *(der),* sometimes referred to as the leverage ratio, the more likely the farm will belong to group B. This makes sense as the debt equity ratio reflects the extent to which farm debt capital is being combined with farm equity capital. It is thus a good indicator of the level of financial risk associated with the farm which again may affect net farm incomes. Furthermore, higher debt capital result in higher interest rates, reducing so agricultural incomes.

A brief description of the predictor variable *typ* will provide a better understanding of the results given below. Farm type '*typ*=1' characterises farms which tend to earn higher incomes on an overall Swiss average, though these are also often subject to higher annual variations. This can be explained – at least in part – by the high interannual variability in the price of pigs (-> pig cycle) and poultry, vegetables and fruit. Farm type '*typ*=0', on the other hand, comprises mainly dairy and arable farms, the product prices of which are subject to weaker market-price changes (this applied at least during the selected study period, when milk prices were not exposed to price fluctuations as great as those experienced recently due to the abolition of the milk-quota system). It thus makes sense that the probability of belonging to group A is higher for the specialist crops than for farms with other production (β_{typ} is positive).

The negative coefficients for *empl* (part-time) in Table 3 depict that the probability of belonging to group A is higher for full-time than part-time farm managers. Other studies (Meert et al., 2005; Lien et al., 2010) have also concluded that off-farm employment affects farm success.

The number of farm branches or activities (*numbranch*) and the age (*age*) and education (*educ*) of the farm manager do, *inter alia,* not significantly impact on the probability of being in either Group *A* or Group *B*. The lack of significance of the farmer's age is borne out in other studies in which the relationship between farmer's age and farm performance are not clear-cut: whereas a number of studies (e.g., Stefanou and Saxena, 1988) have reported a positive correlation between age and efficiency, others (e.g. Kalirajan and Shand, 1985) have noted a non-significant relationship. The study shows that for the analyzed farms, the level of diversification does not play a significant role. This result is somewhat surprising as diversification may reduce risk (e.g. Mesfin et al., 2011 for the case of crop diversification). On the other hand, diversification needs a well-planned long-term strategy, wise enterprise management decisions and may also require additional investments.

In order to give more precise information on probabilities, results gained from fitting logit models are often interpreted using odds, odds ratios, and marginal effects, as these quantities are easy to interpret. E.g., odds above 1 mean that it is more likely that the event occurs (*Y*=1); odds ratios represent the change in estimated odds of an event occurring when the predictor variable increases by one unit.

Table 4 provides odds ratios along with their confidence intervals and the estimated marginal effects for all covariates as incorporated in the panel logit model. Note that the marginal effect (*me)* of fixed effects models can not directly be computed in the *Stata* program but rather has to be approximated as

$$me_j = \widehat{\beta}_j \cdot [\overline{\pi} \cdot (1 - \overline{\pi})] \tag{10}$$

where $\widehat{\beta_j}$ denotes the estimated logistic coefficient of the predictor variable x_j and $\overline{\pi}$ is the average sample predicted probability. In the present study, $\overline{\pi}$ equals 0.272. In the following, a careful interpretation of the log odds and marginal effects as listed in Table 4 is provided.

As the *uaa* increases by one hectare, the odds of belonging to group *A* multiply by 1.081, i.e. increases by 8.1%. The probability to be a member of the successful group *A* increases by 0.015 for a 1ha increase in *uaa* (the marginal effect is 1.015). Despite not statistically significant the model predicts that farms in the mountain region have a much higher probability to remain in the less successful Group B: The odds of mountain farms is only 1.7% of the odds of farms in the plain region. This result is plausible as mountain farms have – due to harsh climatic and orographic constraints – less potential for improvements. This fits well the fact that the odds ratio for the covariate *dpgp* (ratio of subsidies to total gross performance) stays clearly below 1, as *dpgp* tends to be significantly higher in the mountain than in the plain region (see, e.g. Mouron and Schmid, 2011). The numbers listed in Table 4 indicate a strong impact of *empl* (form of employment) on the group allocation. The odd of part-time farm managers is 1/0.006=167 times smaller than for full-time farmers. The significantly lower chance of part-time farmers to stay in Group A is also underlined by the negative marginal effect which suggests π to decrease by roughly 0.8 when switching from full-time to part-time work.

Table 4: As table 3 but for odds ratios. Estimated marginal effects (as calculated with Eq. 8) are given in the last column.

Odds ratio							Marginal effect
	Odds ratio	Std.Err.	z	P>|z|	95% confidence Interval		
reg (2)	1.009	0.473	0.02	0.984	0.403	2.528	0.0018
reg (3)	0.017	0.053	-1.31	0.191	0.000	7.657	-0.808
uaa	1.081	0.041	2.02	0.043	1.002	1.165	0.015
typ	3.842	1.260	4.07	0.000	1.372	6.311	0.266
empl (2)	0.273	0.049	-7.18	0.000	0.191	0.389	-0.257
empl (3)	0.006	0.002	-15.82	0.000	0.003	0.011	-0.822
educ	1.148	0.982	0.16	0.872	0.215	6.142	0.027
age	0.905	0.021	0.87	0.410	0.520	2.134	-0.037
bio	1.571	0.775	0.92	0.360	0.597	4.130	0.089
fracemp	3.463	1.973	2.18	0.029	1.134	10.579	0.246
numbranch	0.982	0.047	-0.38	0.702	0.893	1.079	-0.0037
der	0.168	0.132	-2.26	0.024	0.036	0.787	-0.353
fracgpcat	0.074	0.070	-2.75	0.006	0.011	0.473	-0.517
lapr	7,271,405	9,118,937	12.60	0.000	622,503	84,900,000	3.13
cappr	42.820	32.661	4.93	0.000	9.603	190.941	0.744
landpr	164.554	255.015	3.29	0.001	7.892	3431.184	1.011
dpgp	0.170	0.320	-0.94	0.346	0.004	6.741	-0.351
fraclh	0.741	0.675	-0.33	0.742	0.124	4.418	-0.059
asslu	0.055	0.050	-3.19	0.001	0.009	0.328	-0.573

The results confirm the hypothesis that thanks to a good income from non-agricultural activities, part-time farms probably have less incentive to improve (in the agricultural sector) than do other farms. Full-time farms, on the other hand, depend on achieving considerably higher incomes from agricultural production as quickly as possible, since they have no non-agricultural income to rely on. This finding is supported by Smith (2002), who found that a greater involvement in off-farm labour markets decreases on-farm efficiency. This result is consistent with descriptive statistics (refer to Table 2). The differences between over half-time and full-time farms are by far less pronounced (see the numbers given in Table 4 for *empl(2)* and *empl(3)*).

With a one-unit increase in the logarithm of labour productivity (*lapr*), the odds of belonging to Group A changes by an extremely high factor of approximately 7.3 million, pointing to the fact that increasing *lapr* strongly impacts on the group allocation. Considering the logarithmic transformation (logarithm of the base 10) we conclude from the marginal effect of 3.13 that doubling *lapr* leads to a 0.63 (3.13/5) increase in the probability of being a Group A farm. This result reveals that the (in Switzerland very expensive) factor 'labour' plays a crucial role in whether a farm can rise above the prescribed threshold income of CHF 18'300 during the period under investigation. The other two productivity indices of the full model (capital productivity *cappr* and land productivity *landpr*) play also a significant role - yet clearly less than *lapr* - in predicting the group allocation. Doupling the *cappr* and *landpr* increases the probability to be a member of Group A by 0.15 and 0.2, respectively.

The odds ratio for the predictor variable *typ* is 3.842 (Table 4). Farms of *typ*=1 have 3.84 times higher odds of belonging to Group A than farms with *typ*=0. Specialist-crop farms and finishing farms (*typ*=1) therefore have a distinctly better chance of moving out of the unsuccessful Group B. From the corresponding marginal effect of 0.266 follows that, ceteribus paribus, the probability of being a group A farm is 0.266 higher for specialist-crop and finishing farms than farms of the other farm types (having *typ*=0, see Table 4).

For a 10% change of the proportion of paid labour (*fracemp*), the odds of staying in group A increases by a factor of 0.346 (3.463/10) or approximately 35%. A 10% percent increase of *fracemp* slightly increases the probability of being a member of group A by 0.0246 (=0.246/10).

The predicted odds for group A decreases by 83% [(1-0.168)*100%] when increasing the debt equity ratio (*der*) by one unit, indicating that the farmer should prevent rising the level of indebtedness too much compared to the equity capital. This characteristic is also reflected in the negative value of the marginal effects which indicates a decrease of π by 0.353 per one unit increase of *der*. An increase of the proportion of gross performance from livestock to total gross performance (*fracgpcat*) feeds back negatively of belonging to group A. A 10% increase of *fracgpcat* decreases the probability to be a Group A by 0.052. This is in line with the finding that farms of *typ*=1 (farms with rather low gross performance per hectare such as dairy farms which dominate in Switzerland) tend to have higher probability to stay in group B than farms of *typ*=0.

Performance of the fitted panel data logit model

The classification results using Equation 7 are shown in Table 5. The hit rate of above 85% is significantly above the purely random hit rate of 50%. It is striking that the fitted panel data logistic model is better able to predict the Group A of ‘successful’ farms than the Group B of unsuccessful farms.

Table 5: Cross-classified table of observed and predicted group affiliation. Note that only 5067 out of the 16367 observations has been used for fitting the model.

	Predicted		
Observed	Group A	Group B	**Correct (%)**
Group A	3191	199	**94.1**
Group B	487	1190	**71.0**
Total (%)	**86.5**	**85.7**	**86.5**

The residual analysis of the final model shows a satisfactory model fit (not shown). The leverage of the individual observations makes it clear that most of the observations show no “excessive” leverage, i.e. that the regression function does not “overreact” to most of the observations.

Summary and Conclusions

This paper addresses the development of economically weak farms on the basis of panel data logistic regression. The analysis shows that there are considerable differences between the farms in Group A and B in terms of operational structure and orientation. The study reveals the distinct importance of non-agricultural activities, showing that the likelihood of full-time farms to be a member of group A is particularly high, whilst this is less important for part-time farms having a substantial proportion of non-farm income. Furthermore, the study highlights the importance of high labour productivity in reducing the risk of remaining in Group B. The study further reveals that farms tend to profit from low assets per labour unit, a higher proportion of paid labour and low dept equity ratio, giving some evidence that farming should rather hire labour than investing in (too) expensive machinery.

Further research (and additional data sampling) is needed in order to quantify, e.g., the effect of the farm manager's decision-making process on the economic farm performance.

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