How important are crop shares in managing risk for specialized arable farms? A panel estimation of a programming model for three European regions

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Abstract

We present a dual cost function estimation for total farm cost in a programming model setup, with individual crop shares and expected yields as arguments, estimated simultaneously with risk behaviour. Using large unbalanced samples of specialized arable farms from Northern Italy, the French Grandes Culture Region and Cologne-Aachen in Germany that are observed for at least three consecutive years over the time period 1995-2008, we find a quite satisfactory fit for crop shares and total costs. We implement two model variants where zero crop observations are considered only in the second variant. Our results indicate that the specialized arable crop farmers in the samples use crop shares only to a limited degree as an instrument of risk management. We find moderate technical progress and large efficiency differences between farms.

Keywords

Risk, dual cost function estimation, programming model

1 Introduction

While there is ample evidence that production and market risk matter in agricultural production decisions more generally (Chavas and Pope, 1990; Coyle, 1999), its importance for arable crop share decisions under Western European agronomic and socio-economic conditions might be less clear. Availability of insurance against catastrophic crop failures e.g. caused by hail, often considerable off-farm income sources, risk-free subsidies under the CAP and access to credits to overcome short-run cash constraints could reduce the importance of crop diversification to manage risk. A diversified crop portfolio has however further advantages such as to reduce costs e.g. by lowering disease pressure.

We estimate econometrically a farm programming model which accounts for both the risk and cost effects where farmers maximize expected utility in a classical mean-variance approach (E-V), facing a set of resource and institutional constraints. We allow for not binding constraints and use implicit information contained in non-observed crops. Specifically, we estimate simultaneously a farmer's risk aversion coefficient, the parameters of a dual total quadratic cost function and lag and lead operators for crop shares, technical progress and efficiency differences between farms and, implicitly, the dual values of the constraints. To our knowledge, we present the first simultaneous estimation of a dual cost function with lags and leads in crop shares to account for potential cost impacts of crop rotations combined with a risk analysis.

2 Literature review

Coyle (1992) and Chavas and Pope (1985) provide the theoretical justification to apply the expected utility hypothesis to model farmer's choices under price uncertainty. Chavas and Holt (1990) extend their work by deriving an acreage decision function for two crops under both price and yield uncertainty. Pope and Chavas (1994) show that cost minimisation conditional on the expected quantity (ex-ante cost function) fits the theory, subject to technological restrictions commonly satisfied in agriculture. Pope and Just (1998) extend that framework by introducing non constant returns to scale under production risk. Coyle (1999) propose a non-linear mean variance approach (non-constant absolute risk aversion behaviour) to model the farmer's choices under price and yield uncertainty. Since those pioneering works most of the empirical studies available have econometrically estimated either a dual utility function (Oude Lansink, 1999, Sckokai and Moro, 2006) or taken the production function explicitly into account (Serra et al., 2006, Koundouri et al. 2009, Femenia et al., 2010). Another branch of literature aims at integrating risk behaviour into the Positive Mathematical Programming (PMP) framework (Howitt 1995, for a recent review see Heckelei et al. 2012). Heckelei and Britz (1998) present the first attempt in this direction in a working paper. They introduce a covariance matrix of revenues in the PMP calibration phase and perform a sensitivity analysis with different risk aversion coefficients, finding little evidence that accounting for risk improves the dual values of the calibration constraints. Paris and Arfini (2000) introduce an exogenous absolute risk aversion coefficient and simulate some policy measures on a small sample of Italian farms. Petsakos and Rozakis (2015) calibrate a non-linear mean-variance model by a three-step PMP procedure for a single farm, recovering under a linear cost function what they call the 'true' variance-covariance matrix of revenues. Following the paper of Heckelei and Wolff (2003), which propose to estimate directly the parameters of a mathematical programming model, Cortignani and Severini (2012) provide an empirical application of an expected utility maximization model based on the first order conditions (FOCs). They estimate a non-linear cost function and a farm specific risk aversion coefficient for 27 Italian crop farms by the Generalised Maximum Entropy (GME). They do not separate output price from yield risk and their GME estimation results on such a small sample are most likely strongly dependent on the support values. Jansson *et al.* (2014) apply a Bayesian methodology to estimate the parameters of a farm level mean-variance model which exhibits decreasing absolute risk aversion (DARA) preferences. Their large scale application across EU Member States uses data from the Farm Accountancy Data Network (FADN), but the conference paper does not yet present any estimated results on risk preferences.

Our work extends these studies in several directions. We account separately for price and yield uncertainty; introduce yields and crop shares separately as arguments in the cost function and use an expectation model for crop prices and yields. Lags and leads are considered to catch cross year effects of crop choices on costs. We estimate on a per acreage basis to avoid scale bias. In addition, using large rotating panels allows us to estimate without any a priori information on parameters. Specifically, the model is estimated for three different sets of farm-level data observed over the period 1995-2008 from three European Union (EU) agricultural intensive regions: Northern Italy, Cologne-Aachen area in Germany and the Grandes-Culture region in northern France. We consider all reported farm costs with the exemption of land rents[1] in the dual cost functions such that there are neither so-called "unobserved costs" nor a priori-allocation of certain cost items to production activities.

3 Model and estimation approach

We assume expected utility maximisation in a classical mean-variance approach subject to a set of resource and institutional constraint:

$$\max_{\mathbf{s}} EU/L = E(\tilde{\mathbf{p}}\,\mathbf{yld})'\mathbf{s} + \mathbf{sub}'\mathbf{s} + dsub - c(\mathbf{s}, E(\mathbf{yld})) - 0.5\alpha\boldsymbol{\sigma}_R^2(s)$$

$$\text{subject to} \qquad \mathbf{As} \le \mathbf{b}/L \quad (\boldsymbol{\gamma})$$

$$\mathbf{0} \le \mathbf{s} \le \mathbf{1}$$

where, EU is expected utility, $\tilde{\mathbf{p}}$ and $\mathbf{yld}$ the vector of random output prices and yields, E the expectation operator, $\mathbf{s}$ the vector of crop shares as the decision variables, $\mathbf{sub}$ the vector of coupled subsidies per hectare and $dsub$ the decoupled subsidy per hectare, L land

[1] The reader should note that FADN reports the amount of work performed by family members, but there are obviously no direct accounting costs linked to that labour use. We report in section 5.6 on impacts of family labour per ha on estimated farm specific efficiency parameters.

endowment, $c(\mathbf{s}, E(\mathbf{yld}))$ the per ha cost function representing the total farm costs excluding family labour and land rent, α the coefficient of risk aversion, σ_R^2 the endogenously determined variance of farm revenue per ha and $\mathbf{A}$ the matrices of resource use per unit of quantity and $\mathbf{b}$ the right hand side depicting resource endowments and institutional bounds with associated shadow prices $\boldsymbol{\gamma}$. Note that we consider utility per managed ha which implies that our cost function is homogenous of degree one in total acreage. The parameters of the cost function as well as the risk aversion coefficient and the shadow values of the constraints are estimated directly on Karush-Kuhn-Tucker (KKT) conditions representing the FOCs.

3.1 Empirical model

Price expectations are estimated beforehand using adaptive expectations (Chavas and Holt, 1990; Sckokai and Moro, 2006) based on crop prices equal across farms to avoid endogeneity problems. Crop group prices are defined on Törnqvist indeces. Farm level yield expectations are modelled by adjusting the expected regional yield by the ratio between the average farm yield and the average expected regional one, considering only years where the crop is observed on that farm. Expected regional yields are the predicted values of regressions on a quadratic trend, removing the quadratic or even linear coefficients if these are not significant.

Our dual quadratic cost function covers all reported costs besides those of renting land. Some costs are not linked to actual input purchases, such as depreciation. To exploit information on observed crop shares and expected yields, we introduce both as arguments in the cost function, assuming a two-stage decision process where first expected yields are decided upon.[2] Differently from typical PMP approaches, we do not assume a Leontief relation between certain variable cost items and acreage. The quadratic part of the cost function per hectare for farm *f* in year *t* is specified as followed:

$$cq_{ft} = \overline{\mathbf{x_{ft}}}'\mathbf{Q_1 yld_{ft}} + \overline{\mathbf{x_{ft}}}'\mathbf{Q_2 yld_{ft}^2} + \overline{\mathbf{x_{ft}}}'\mathbf{Q_3 \bar{s}_{ft}} \qquad (1)^3$$

Where, Q are symmetric matrices of dimension $I \times I$, being I the number of crops grown in the area where the farm is located, Q_1 is a diagonal matrix which measures the effect of expected yields yld on costs, Q_2 captures the same for the square of expected yields and Q_3 accounts for own and cross effects of crop shares on costs. $\bar{x}$ and $\bar{\mathbf{s}}$ are the vectors of farm optimal average expected output quantities and average crop share respectively and L is the land endowment of the farm. The farm average production quantities $\bar{x}$ and crop share $\bar{\mathbf{s}}$ in a year are a linear combination of last, current and next year's production quantity and crop share respectively; in order to capture potential crop rotational effects on the costs. The weights for the previous and last year are endogenously estimated.

Changing the output x of product i in the year $t-1$ or $t+1$ can hence impact current year costs, e.g. for fertiliser or crop protection. The lags and leads might also capture differences between the accounting period in FADN and the actual cropping year. A Cholesky

[2] Estimating an alternative model where yield decisions are endogenous did not yield satisfactory results. Modelling yield decisions at the single farm would require information on farm characteristics determining the relation between input use and yields, such as soil type and micro-climate. Simply introducing a farm specific constant for each crop and farm to capture the impact of such non-observable factors would potentially overfit the whole model as we have typically only between 5 and 7 observations per farm, and even fewer for individual crops. We therefore opted to rather treat expected yields as fixed.

[3] For notation easiness we omit the E operator in all the following equations and we use p, yld and x to indicate expected price, yield and quantity respectively if not differently specified.

decomposition of Q_3 ensures positive definiteness and hence convexity (Howitt and Paris, 1998). Definiteness of the matrices Q_1 and Q_2 relating to yields is not required as yields are not decision variables.

The linear part of the costs function consists of (1) a term for fixed costs on the farm, $cfix$, (2) a term for variable costs per unit produced cv, and (3) fixed costs per ha of land ch to account for costs for basic field operations.

$$cl_{ft} = cfix + \mathbf{cv'}\overline{\mathbf{x_{ft}}} + ch\, L_{ft} \tag{2}$$

The sum of the quadratic, cq, and the linear term, cl, is multiplied by a general farm input price index, px, taken from Eurostat database and by a technical progress term, $(1+\delta t)$. We also added a farm specific scaling factor, cf_f, which measures cost efficiency across farms.

The cost function and the overall optimization problem is expressed on a per-hectare basis. The specification of the farm cost function per hectare is:

$$c_{ft} = \left[(cl_{ft} + cq_{ft}) * px_t * (1+\delta t) * cf_f \right] / L_{ft} \tag{3}$$

Deriving the farm cost per hectare with respect to output quantities (equation 4) leads to crop marginal costs which depend on the constant term cv, the expected yield of that crop according to the diagonal elements of Q_1 and Q_2, and the crop share mix according to Q_3. In addition, farm cost per ha change over time according to the product of px and δt while accounting for farm specific effects according to cf.

$$\frac{dc_{ft}}{dx_{fti}} = \left[\left(cv_i + Q_{1ii} yld_{fti} + Q_{2ii} yld_{fti}^2 + Q_{3i}{}'\mathbf{s}_{ft} \right) px_t\ \delta t\ cf_f \right] / L_{ft} \tag{4}$$

The reader should note here that the cost function in (3) and its derivative in (4) depend on *crop shares* and not, as usual in PMP, on acreages, such that marginal production costs do not increase linearly in total farm acreages. There are no “unobserved” costs, (3) depict all accounting costs, the difference between revenues plus subsidies minus these costs as the farms’ profit defines the returns to land and other binding constraints in the model. Note that the profit remunerates not only own and rented land, but also family labour and other assets for which no accounting costs are reported, such as capital stock which is depreciated according to tax laws.

The variance of farm revenues per ha, σ_R^2, is modelled by separating the variance of yields from the variance of prices according to Coyle 1999:

$$\sigma_R^2 = \frac{\mathbf{x'}}{L} \mathbf{V}_p \frac{\mathbf{x}}{L} + \mathbf{p'V}_x\mathbf{p} + \sum_{i=1}^{5}\sum_{j=1}^{5} V_{p_{ij}} V_{x_{ij}} \tag{5}$$

where $\mathbf{V}_p$ is the variance-covariance matrix of crop prices and $\mathbf{V}_x$ is the variance-covariance matrix of quantity per ha produced based on farm level data. The variance-covariance matrix of prices was computed from sample mean series of market prices over the period 1995-2008 after de-trending by the Consumer Price Index. Coupled subsidies are not taken into account in the variances, but considered as deterministic.

The variance-covariance of crop yields is derived from farm level data to avoid underestimation due to aggregation bias (Just and Weninger, 1999). Farm level yields are de-trended by using the regional trend estimates; the variance-covariance matrix is then computed from the de-trended yields after substracting farm specific crop mean yields. Covariances between crop price and yield variability are assumed zero as we consider internationally traded crops which were additionally under administrative price schemes for a larger part of the observation period (Serra et al., 2006).

The constraints cover a land balance (equation 6), compulsory set aside where applicable and sugar beet quota (equations not shown):

$$\sum_i \mathbf{s}_{fit} \leq 1[\gamma] \qquad (6)$$

Finally, expected output quantities in a year are the product of estimated expected yields and endogenously determined acreages: $x_{fit} = s_{fit}\, L\, yld_{fit}$. The FOCs for the optimal land allocation without accounting for set aside obligation and sugar beet quota are hence:

$$E\left[p_{fti}\, yld_{fti}\right] \leq \frac{dc_{ft}\left(s_{fit}\right)}{d(s_{fit})} + \frac{\alpha d\left[\sigma_R^2\left(s_{fit}\right)\right]}{d(s_{fit})} + \gamma \perp s_{fti} \geq 0 \qquad (7)$$

Note again that decision variables are crop shares at a given land endowment and that the optimisation problem is expressed on a per-ha basis. We consider measurement errors for the acreages which together with the error on the estimated average costs per ha enter the estimator, but do not assume allocation errors.

3.2 Corner solutions in crop choice

Single farm data comprise frequently zero observations, in the PMP literature termed as the "self selection problem" (Paris and Arfini 2001). We propose here a distinction between the case where the crop is observed on a farm only in some of the years the farm stays in the sample and the case where the crop is never observed. In the first case, it is relatively straightforward to develop yield expectation for all years. The second case is clearly more challenging as discussed next and not considered by us.

In the absence of measurement errors, a zero observation implies that marginal costs exceed marginal profits respectively utility. The majority of authors however calibrate such that marginal costs and profits are equal; we do not see any good reason for doing that. Furthermore, as typical PMP type models require information on gross margins, yields and allocated costs per crop, the sample mean of these items is typically used for the missing crops. The most obvious reasons for not growing a crop is that soil and climate condition in that farm disfavour that crop compared to average conditions, be it by lower than average yields or higher than average costs. We hence do not consider crops in farms where they are never observed, avoiding the introduction of arbitrary yield information. However, if a crop is observed on a farm in one or several of the years, we estimate the expected yield. The only difference to crops observed in all years is hence the number of observations underlying the mean calculations.

The KKT-conditions allow marginal costs to exceed marginal profits respectively utility for zero observations such that non-observed crops in a specific year typically contribute less information. In opposite, as long as positive acreages are estimated for observed crops, marginal costs and expected marginal utility must be equal.

3.3 Technical implementation of the estimator

Due to the Cholesky decomposition and quadratic terms, the estimation procedure is highly non-linear. Along with the KTTs, no closed form representation of (4) exists. We therefore estimate in GAMS which offer solvers for this class of estimation problems. Specifically, we benefit from the so-called EMP (Extended Mathematical Programming, Ferris et al. 2009) package which allows inter alia defining bi-level programming problems. The outer optimization problem in our application is the statistical estimator which searches for best-fit parameters, while the inner one depicts the maximization of expected utility for each farm at given parameters. EMP automatically generates the FOCs, while GAMS offers transparent interfaces to performing Non-Linear Programming solvers such as CONOPT (Drud A. 1992).

4 Data

We use FADN data over the period 1995-2008 for three European agricultural intensive regions: Northern Italy, Cologne-Aachen in Germany and the Grandes-Culture region in northern France. These rotating panels consider arable farms observed at least three consecutive years which produce cereals, oilseeds, sugar beet and, for Germany only, potatoes; these crops represent the dominant production system in these regions. Farms producing specialty crops such as vegetables are excluded as their technology (e.g. land-man ratio) is rather different from the considered crops. Equally dropped are observations with animal or fodder production, observations below 10 hectares of farmland and where total costs exceed revenues over the observation period. The final samples includes 1,635 observations for 351 farm in Northern Italy, 784 observations for 125 farms in Cologne-Aachen and 1,565 observations for 218 farms for the Grandes Culture region. We distinguish five crop categories: wheat, corn, other cereals, oilseeds and sugar beet; in Germany, potatoes are added. We also consider compulsory and voluntary set aside.

Italian farms are in average the least diversified with an average number of crops grown per farm of 2.3 and 28% of the observations with only one crop in a year. 17% of the farms even grow only one crop, 83% of these observations relate to corn. Corn is also the crop with the highest average share on farmland, 57%, and is found in 92% of the observations. Oilseeds are the second most grown crop category, followed by wheat. Although more than one third of the observed Italian farms grow sugar beet, the crop covers only 7% of the farmland on average.

Rather differently, only one observation in the German sample and none in the French sample shows monoculture. These differences could reflect the larger average farm size of French and German farms, 95 and 123 hectares respectively, compared to 41 hectares for Italian ones. The average number of crops grown on German farms in the sample is 3.2 and 3.8 in the French sample. In both samples, wheat has the highest share and observed in almost all farms. In Germany, sugar beet has the second highest share, grown by almost all farms, followed by other cereals. In France oilseeds takes the second place both in terms of share (21.7%) and in terms of adoption (93%). A larger share of French farms grows also other cereals and sugar beet besides wheat and oilseeds.

The average number of family working units per farm is around 1.2 in all the three samples, while hired labour differs: it is employed in 9% of the Italian farms only, used in 29% of the French and more than half of the German farms. Total accounting costs per hectare, excluding land rents, are higher in Germany (1,168 euro) compared to Italy (952 euro) and France (865 euro) which might be explained by the larger employment of hired labour and by the large percentage of German farms that grow sugar beet, and the inclusion of potato cropping.

Time series data on regional yields used to compute the covariance matrix of yields are taken from the Eurostat database. The covariance of prices uses the sample mean of crop prices over the period 1995-2008.

5 Empirical results

5.1 Fit and supply elasticities for Italy

Table 2 reports the fit for Italy, with R2s as usual calculated from deviations from the sample mean. As perhaps expected, if corner solution in the yearly crop choice are considered (model 2), the fit both for crop shares and costs drops significantly.

Table 2: Model fit (R2), Italian regions

	Model 1		Model 2	
	Acreage	Costs	Acreage	Costs
cwheat	52,30		24,50	
corn	77,60		53,32	
othcer	53,43		23,27	
oil	56,98		24,56	
sbeet	99,34		78,14	
setas	56,36		62,89	
Total		73,38		64,34

Source: Own calculation

Note: Model 1 considers a crop on a farm only in years where it is observed, model 2 considers a crop in all years on a farm if it was observed at least in one year on that farm.

The R2 of both the estimated crop shares and total farm costs is relatively high for a single farm panel estimation, especially considering that the efficiency multiplier is the sole farm specific parameter. That multiplier is certainly one reason for the good fit of total costs. [4]
In the second model, we allow the estimator to also introduce crops in years where they have not been observed on a farm if that farm has grown that crop at least in one year during the period it stays in the sample. The problem is clearly that we do not have observations on yields for these years such that we use estimates (see section 3.2 for details). The reader should also note again that the information from the zero observations is weaker compared to non-zero ones: it only implies that the marginal costs plus the marginal risk term is (probably) above the marginal revenue.

Table 3 reports the supply elasticities for the two models; their magnitude is similar to those found in other studies. Besides sugar beet, whose production is subject to a quota, we find as expected that the crop with the highest share in the sample, namely corn, has the lowest supply elasticities. Equally, considering the additional flexibility of introducing crops also in years where they are not observed, drives up the elasticities. A perhaps astonishing finding is the fact that an increase in the wheat price leads to a drop in the land rent (in average of the sample), which can be explained by the indirect effect of the wheat price increase on the risk term. In some cases, we even find profit decreases if a price increases, which is impossible in a profit optimization framework. However, with risk aversion, a crop might be expanded even to a point where profit decrease if the risk reduction effect of that expansion is large enough. That effect is however small and only found for the second model where the risk aversion coefficient is higher (see also section 5.4 below).

[4] The reader should note again here that there are no constant terms relating directly to crop shares, instead the costs function parameter indirectly drive optimal allocation decision. Equally, we estimate the fit for crop shares and not for the observed acreage, there is hence no artificial increase in the explanatory power by adding a land balance. Indeed, if we minimize the variance of the observed acreages instead of crop shares, the R2 of all crops are close or above 90%. That point should be carefully considered if our results are compared to other studies.

Table 3: Price elasticities of supply and economic indicators, Italian regions

	cwheat	corn	othcer	oil	sbeet
cwheat	**0,86**	-0,81	-0,03	-0,17	-0,01
	2,45	*-1,59*	*-0,11*	*-0,98*	*0,00*
corn	-0,13	**0,52**	-0,02	-0,16	-0,01
	-0,22	***0,73***	*-0,03*	*-0,20*	*-0,02*
othcer	-0,28	-1,02	**0,62**	-0,20	-0,04
	-1,01	*-2,09*	***1,25***	*0,18*	*-0,06*
oil	-0,15	-0,81	-0,02	**0,77**	-0,01
	-0,83	*-1,20*	*0,02*	***1,62***	*-0,01*
sbeet	-0,01	-0,06	0,00	-0,01	**0,13**
	0,00	*-0,07*	*0,00*	*0,00*	***0,16***
setas	0,00	-0,04	0,00	-0,03	0,00
	0,00	*0,00*	*0,00*	*0,00*	*0,00*
Land rent	-0,07	1,13	0,06	0,15	0,02
	-0,22	*0,92*	*0,09*	*0,51*	*0,04*
Utility	0,37	2,22	0,05	0,41	0,65
	0,62	*4,45*	*0,07*	*0,71*	*1,18*
Profit	0,11	1,17	0,01	0,11	0,29
	0,05	*1,47*	*-0,01*	*-0,01*	*0,27*
Total costs	0,01	-0,04	0,00	0,04	0,00
	0,03	*-0,23*	*0,00*	*0,12*	*0,00*
Revenues	0,08	0,73	0,00	0,09	0,19
	0,07	*0,81*	*-0,01*	*0,06*	*0,18*

Source: Own calculation

Note: First number in each cell for Model 1, second number in italics for Model 2

5.2 Fit and supply elasticities for Germany

The results for Germany with regard to the R2 are shown in table 4. Generally, the fit is below the one found for Italy, differences between the two model variants are much smaller, and, in some cases, the fit is even improved if zero observations are considered.

Table 4: Model fit, German regions

	Model 1		Model 2	
	Acreage	Costs	Acreage	Costs
cwheat	53,09		43,88	
corn	20,90		30,58	
pot	27,69		17,33	
othcer	24,48		34,50	
oil	35,32		45,75	
sbeet	100,00		98,28	
setas	57,65		69,06	
Total		48,03		48,22

Source: Own calculation

The latter might reflect two combined effects of including missing observations: first, the variance of the crop shares is increasing while second, it is sufficient for the estimator to estimate marginal costs exceeding marginal revenues to drive the crop share to zero, and not, as in cases of an interior solution, to equilibrate both. The lower fit compared to Italy might stem from the fact the considered regions in Germany are less uniform in cropping conditions and that farms tend to be less specialized. Whereas in Italy, corn is really the dominating crop, average crop shares in our German sample are more balanced and the variances are somewhat higher. In addition, the lower fit for the costs may be explained by the longer average period German farms stays in the panel (6.2 years) compared to Italian ones (4.7 years).

The supply elasticities in Germany (Table 5) show a similar pattern as the values for Italy: the dominating crop in the sample, wheat, has a low supply elasticity, while corn, which has a low share in Germany, shows a high value. Considering zero-observations has however here no uniform effects: in some case, elasticities increase (wheat, corn), while for other crops they decrease (potatoes, other cereals, oilseed). The elasticities of land rent, utility and profit with respect to crop prices show a positive sign, as expected, for both model variants.

Table 5: Price elasticities of supply and economic indicators, German regions

	cwheat	corn	pot	othcer	oil	sbeet
cwheat	**0.43**	0.00	-0.03	-0.20	-0.04	0.00
	0.69	*0.00*	*0.00*	*-0.40*	*0.00*	*0.00*
corn	-0.47	**1.28**	-1.65	-0.46	-0.08	0.00
	-7.33	***6.01***	*0.00*	*0.96*	*0.00*	*0.00*
pot	-0.09	-0.01	**0.47**	-0.02	0.01	0.00
	0.00	*0.00*	***0.06***	*0.00*	*0.00*	*-0.04*
othcer	-4.21	-0.01	-0.09	**4.17**	0.00	0.00
	-3.19	*0.00*	*0.00*	***2.36***	*-0.04*	*0.00*
oil	-0.34	0.00	0.03	0.00	**0.33**	0.00
	-0.02	*0.00*	*-0.09*	*-0.06*	***0.12***	*0.00*
sbeet	0.00	0.00	0.00	0.00	0.00	**0.00**
	0.00	*0.00*	*0.00*	*0.00*	*0.00*	***0.00***
Land rent	0.47	0.00	0.09	0.39	0.13	0.00
	0.32	*0.00*	*0.40*	*0.00*	*0.02*	*0.32*
Utility	0.74	0.00	0.25	0.03	0.08	0.91
	0.12	*0.00*	*0.25*	*0.08*	*0.00*	*0.00*
Profit	0.74	0.00	0.25	0.03	0.08	0.91
	0.17	*0.00*	*0.27*	*0.02*	*0.01*	*0.22*
Total costs	0.09	0.00	0.05	-0.01	0.00	0.00
	0.17	*0.00*	*0.27*	*0.02*	*0.01*	*0.22*
Revenues	0.43	0.00	0.17	0.01	0.04	0.45
	-0.13	*0.00*	*0.00*	*-0.11*	*-0.01*	*0.00*

Source: Own calculation

5.3 Fit and supply elasticities for France

The fit for the models (Table 6) is similar to the results of Germany, i.e. worse than Italy, with the difference that the fit for cost by the second model exceeds that one of the first. Besides sugar beet, whose production is bounded by the quota, the two most grown crops in France, wheat and oilseeds, show the lowest supply elasticities, similar to the results found for Italy and Germany (Table 6).

Table 6: Fit, price elasticities of supply and economic indicators, French regions

	cwheat	corn	othcer	oil	sbeet
cwheat	**0,59**	-0,04	-0,40	-0,09	-0,01
	0,19	*0,00*	*-0,07*	*0,00*	*0,01*
corn	-0,54	**1,05**	-0,22	-0,21	-0,01
	-0,21	***0,92***	*-0,05*	*0,09*	*0,24*
othcer	-1,42	-0,06	**1,52**	-0,13	0,00
	-0,32	*-0,08*	***0,47***	*0,02*	*-0,01*
oil	-0,23	-0,05	-0,10	**0,34**	-0,01
	0,00	*0,07*	*0,10*	***0,46***	*0,06*
sbeet	-0,01	0,00	0,00	-0,01	**0,08**
	0,01	*-0,25*	*-0,39*	*-0,77*	***-0,17***
setas	-0,01	-0,06	-0,07	-0,05	0,00
	-0,06	*-0,69*	*-0,19*	*-0,04*	*0,00*
Land rent	0,22	-0,02	-0,03	0,21	0,01
	0,59	*-0,01*	*-0,04*	*0,44*	*0,03*
Utility	0,64	0,06	0,18	0,24	0,35
	1,94	*0,20*	*0,59*	*0,76*	*1,14*
Profit	2,38	0,22	0,39	0,45	1,21
	1,94	*0,20*	*0,59*	*0,76*	*1,14*
Total costs	-0,09	-0,01	0,03	0,06	-0,02
	0,06	*0,00*	*-0,02*	*-0,03*	*-0,01*
Revenues	0,46	0,04	0,11	0,15	0,25
	0,46	*0,03*	*0,09*	*0,08*	*0,25*

	Model 1		Model 2	
	Acreage	Costs	Acreage	Costs
cwheat	41,11		13,87	
corn	25,93		23,31	
othcer	20,22		20,62	
oil	50,59		44,41	
sbeet	96,49		99,72	
setas	70,59		86,24	
Total		64,31		71,07

Source: Own calculation

5.4 Risk effects

As indicated in formula (6) and seen from the FOC in (7), we measure the trade-off between profit and risk on a per hectare basis. Doubling the farm size L and, as a consequence, all crop acreages, leaves the optimal crop allocation unchanged[5]. Hence, the farmer considers production and market risk independent of firm size.
The findings with regard to risk behaviour are country, and partly model dependent. We find no risk effect on crop share decisions in German farms, whereas Italian farmers act risk adverse. Results for France are ambiguous: a quite high risk aversion coefficient is estimated in the first, but none in the second model variant. These results might hint at data problems; there had been e.g. Pillar 2 programs in France which promoted oilseeds, which we could not include in our estimation, but might influence the outcome. The risk aversion coefficients in Italy might seem relatively low, but in the second model, some price increases can also trigger profit decreases while utility increases, underlining a distinct impact of the risk term on allocation decision.

Differences in risk attitude between the samples might also reflect farm sizes: the larger farm size in Germany and France leads in average to a higher number of crops on a farm, and changing their shares might have a limited impact on overall production and market risk. With the limited farm size in Italy, risk considerations might play a higher role and are consequently identified by the estimator. The very high share of corn in many farms might also help the estimator to assess the costs for highly specialized cropping management. One might conclude that crop diversification plays a minor role as a risk management tool in specialized arable cropping. However, our estimation of the co-variance matrix for the yields might not be stable enough for a rotating panel with a limited number of observations per farm.

Table 8: Estimated risk aversion coefficients

	IT	DE	FR
Model 1	0,014	0,000	0,061
Model 2	0,019	0,000	0,000

Source: Own calculation

5.5 Farm specific efficiency parameters

We find technical progress, measured as a linear decrease in costs per ha, of around 1% in Italy, 1.4% in France and 1.7 % in Germany. While our model assumes constant returns to scale within a farm, it allows for efficiency differences across farms based on the efficiency parameter. In order to test scale and family labour effects on cost, we regress the farm specific efficiency multiplier for the first model variant on farm size and farm's family labour per hectare. Results (see table 9) suggest that family labour per hectare does not affect total farm costs. This is surprising as more family labour could substitute for hired one. One reason could be poor data quality on family labour use, another one an indirect effect as small farms shows a higher family labour per ha ratio. The effect of farm size in ha is negative and significant at 10% significance level in the German sample, while it is positive and significant

[5] Indeed, one could alternatively argue that we estimate a model where wealth is proportional to the farmland assets. Attaching a uniform value per ha of farmland, w, to all farms in the sample should leave our estimation results unchanged besides leading a different scaling of the risk coefficient. In addition, if we add the expected profit per hectare to the farmland value per hectare we end up with: $\left[0.5\alpha\boldsymbol{\sigma}_R^2(\mathbf{s})\right]/((w+E(\tilde{\mathbf{p}}\,\mathbf{yld})+\mathbf{sub}+dsub-c(\mathbf{s},E(\mathbf{yld}))$. However, this formulation leads to the same results of the more simplified expression $\left[0.5\alpha\boldsymbol{\sigma}_R^2(\mathbf{s})\right]/w$ as the expected profit is expected to be much lower than farm wealth and the amount of expected profit which remains on the farm, and thus increase the farm wealth, after withdrawing for farm household consumption is small.

at 1% level in Italy and France (see table 9 below). But impacts are in all cases quite small which might indicate that farm size has indeed a limited impact on costs on specialized arable farms. Considering that average family labour use in the three samples is rather similar, that implies that profits per family AWU increase with farm size as long as the share of owned land stays constant, which underlines that structural change needs not necessarily be driven by scale effects relating to accounting cost, at least as important can be scale effects of (family) labour use.

Table 9. Regression of the farm specific efficiency parameter in the three samples

	Italy	Germany	France
UAA (ha)	0.0010***	-0.0012*	0.0013***
family labour (units/ha)	-0.3706	0.0485	4.2037
constant	0.9218***	1.1271***	0.5084***

*, **, *** indicates 10%, 5% and 1% significance level respectively

5.7 Lags and leads in crop shares and production quantities

To our surprise, we find no or negligible small estimated lag and lead effects. We fear that our farm samples do not provide enough relevant variance: changes in crop shares from year to year are probably too small to distinguish the average impact of crop shares in a year on costs from the differences in these shares to previous and last year. Furthermore, as we need shares also for the first and last year for the observation of each farm to drive our cost function, either the lag or the lead observation drops out for these observation and the weights for the remaining two years have to scaled up to unity instead. We are therefore cautious to conclude from these estimates that cost saving effects of crop rotations do not exist in the sample.

6. Summary and conclusion

We present an estimation of the parameters of an expected utility programming model based on the FOCs, allowing for non-binding constraints and zero activity levels. We employ a quadratic cost function for total farm cost, assuming a two stage-decision process where first yields and next the optimal acreage allocation are decided upon. We model only the second step, which allows us to exploit information on observed crop acreages and yields and to introduce an explicit land balance and institutional constraints in the estimation. The acreage variable in the cost function is a linear combination of previous, current and next year allocation to account for cross year effects. We normalize by total farmland in order to avoid scale bias. Risk accounts separately for price and farm-level yield variance. We use rotating panels of arable farms from three EU agricultural intensive regions over the period 1995-2008, considering farms which stay at least three consecutive years in the panels. We find quite satisfactory fit for crop acreages and costs in our estimation and reasonable values of supply elasticity. Our results seem to indicate that the specialized arable crop farmers in our sample are not or to a limited degree using crop shares as an instrument of risk management. Specifically, we find no risk aversion in Germany, small aversion in Italy, and ambiguous results for France. There is little evidence for lag and lead effects of production quantities and cropping shares on current year accounting costs. Our cost function, defined on per ha basis, is homogenous of degree zero in total farm acreage such that the farm specific efficiency multiplier can capture scale effects. However, we find negligible small scale effect with regard to total acreage and no significant impact of family labour use per ha on farm costs per ha.

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