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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Summary

We estimate a dual cost function together with farmers' risk attitude in a programming model setup which allows for zero activity levels and not binding constraints. We use crop shares as decision variables in order to avoid scale bias and to shed light on farm risk management strategies. The model is estimated for three unbalanced panels of specialized arable farms observed for at least three consecutive years in Northern Italy, Cologne-Aachen region in Germany and the Grandes-Culture Region of France over the time period 1995-2008. Our estimated models show quite satisfactory fit with regard to crop shares and costs while results indicate that specialised arable farms from these regions use crop shares only marginally as a risk management instrument. The supply elasticities with respect to price show values in a reasonable range. The cost reducing effects of farm size measured in hectare is neglectable and, as expected, we find a positive correlation between farm size and the number of crops grown in a year.

Keywords: risk behaviour, cost function estimation, programming model
JEL Classification codes: Q12, C61, C33

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1 INTRODUCTION

While there is ample evidence that production and market risk affects agricultural production decisions (Chavas and Pope, 1990; Coyle, 1999), its influence on 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 Common Agricultural Policy (CAP) and access to credits to overcome short-run cash constraints could reduce the importance of crop choice and crop diversification as a risk management instrument. Furthermore, in order to benefit of similar machinery requirements and management, farmers might only consider some arable crops in their portfolio and not all the ones actually grown in the area where the farm is located. The production and even market risk of the considered crops might be positively correlated such that the risk reduction effect of less specialized yearly crop shares could be limited.

Yearly crop diversification may not only be an instrument of risk management, but it may also impacts crop specific costs by crop rotations which help to maintain soil fertility and to manage pests. While yearly crop diversification always implies rotations, the opposite is not true. Indeed, farms with less plots then the length of the rotations cannot fully use their potential to reduce farm risk. In extremum, small farms are likely to manage only one single plot. Neither the number of plots managed by the farmer nor farm's rotations are included in the publicly available database, hence crop rotation is often an omitted variable in the econometric studies on farm behaviour. Hence, an empirical analysis that accounts simultaneously for the effect on farm's risk of the crop shares decision in a specific year and the potential cost reducing effect of crop rotations is challenging. We try to address this issue by using farm's crop shares as decision variables in our farm programming model which accounts for both the risk and the cost effects of farmer's choices. The model is econometrically estimated by a least squares procedure in a programming framework. It assumes that farmers maximize expected utility from profit under risk in a classical mean-variance (E-V) approach

(Freund, 1956, Coyle, 1992 and 1999) facing a set of resource constraints plus institutional constraints from the CAP. We allow not-binding constraints and use the implicit information contained in zero activity levels for some crops in some farms. Specifically, we estimate simultaneously a farmer's risk aversion coefficient, the parameters of a dual total quadratic cost function and the lag and lead operators for the effects of last and next year crop shares on this year farm's costs, the parameters of technical progress and of efficiency differences between farms and, implicitly, the dual values of the constraints. To the best of our knowledge, we present the first simultaneous estimation of a cost function which includes a moving average of crop shares to account for potential crop rotational effects under a set of potentially not binding constraints combined with a risk analysis.

2 LITERATURE REVIEW

The attention paid to the role of risk in driving farmer's choices dates back to the agricultural economics literature of the '70s when both first theoretical works and empirical applications reflecting risk behaviour on representative farms were published. Chavas and Pope (1985) and Coyle (1992) provide the theoretical justification to apply the expected utility hypothesis to model farmer's choices under price uncertainty. Specifically, the authors demonstrate general properties of input demand and output supply under any type of probability distribution of prices and any kind of risk behaviour, including risk neutrality as a special case. Chavas and Holt (1990) contribute by deriving an acreage decisions function for two crops under both price and yield uncertainty. Their empirical application of the model to an aggregate farm representing the United States over the period 1954-1985 tests and rejects both risk neutrality and constant absolute risk aversion (CARA) behaviour, but support decreasing absolute risk aversion (DARA). Pope and Chavas (1994) show that cost minimisation conditional on the actual observed quantity (ex-post cost function) under production uncertainty is not consistent as it requires ex-ante knowledge about the stochastic production disturbances. Rather, 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 and showed the bias of an ex-post cost function under production uncertainty. 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 (Lansink, 1999; Sckokai and Moro, 2006) or a utility function taking explicitly the production function into account (Serra et al., 2006, Koundouri et al. 2009, Femenia et al., 2010).

A rather recent research branch is developing to integrate risk behaviour into the Positive Mathematical Programming (PMP) framework (Howitt, 1995), which is a three step procedure to calibrate mathematical programming models (for a recent review on PMP see Heckelei et al., 2012). The first attempt in this direction is made by Heckelei and Britz (1998) in a working paper. The authors introduce a covariance matrix of revenues in the first stage calibration of PMP 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 in the first step of PMP procedure and simulate the effects of 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. Given the ill-posed nature of the problem they use exogenous crop supply elasticities to improve the calibration of the model according to the procedure suggested by Mérel and Bucaram (2010). The authors recover what they call the 'true' variance-covariance matrix of revenue, however their linear cost function implies that the allocation behaviour is solely steered by marginal changes in risk as marginal costs per unit stay constant. Furthermore, they impose strict assumption on risk preferences under their logarithmic utility function which implies a relative risk aversion coefficient of 1. Following the paper of Heckelei and Wolff (2003), which propose to estimate directly the parameters of a mathematical programming model going beyond the standard PMP, Cortignani and Severini (2012) and Jansson et al. (2014) provide an empirical application to the direct estimation of the parameters of an expected utility maximization model based on the first order conditions (FOCs). Cortignani and Severini 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 likely heavily 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. The application is based on the data from the Farm Accountancy Data Network (FADN) and it is a large scale application across EU Member States; but their conference paper does not present any estimated results on risk preferences yet.

Our work belongs to the branch of estimating the parameters of a programming model (Heckelei and Wolff, 2003) while accounting for risk, but it extends the previous studies (Cortignani and Severini, 2012 and Jansson et al., 2014) in several directions. First, we account for both price and production uncertainty and model them separately; second, we introduce crop shares and expected yields separately as arguments in the cost function while applying an expectation model for crop prices and yields in order to avoid the bias from using the realized (ex-post) values (Pope and Chavas, 1994); third, we account not only for current, but also for last and next year’s crop shares in the cost function to catch potential cross year effects of crop choices on costs. Fourth, we estimate on a per acreage basis to avoid scale bias and in such a way we have crop share as farmer's decision variable in the model. In addition, in opposite to many other applications, we allow for not binding constraints and we use large rotating panels of single farm observations over the relative long time period 1995-2008 which allows us to estimate without any a priori information on parameters. 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. Finally, in the dual cost function we consider all farm costs with the exemption of land rents[1] such that there are neither so-called 'unobserved costs' nor a priori allocation of certain cost items to production activities. The latter removes any similarities with classical PMP work.

3 MODEL AND ESTIMATION APPROACH

Our theoretical farm level model assumes expected utility maximisation in a classical mean-variance approach such that the farmer chooses the crop allocation to maximise the profit under risk subject to a set of resource and institutional constraints:

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

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

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

where, EU is the expected utility, $\tilde{\mathbf{p}}$ is the vector of random output prices and $\mathbf{yld}$ the vector of random yields, E is the expectation operator, $\mathbf{s}$ is the vector of crop shares, $\mathbf{sub}$ is the vector of coupled subsidies per hectare and $dsub$ is the value of the farm decoupled subsidy per hectare, L is the land endowment, $c(\mathbf{s}, E(\mathbf{yld}), px)$ is the per ha cost function representing the total farm costs excluding family labour and land rent as a function of crop allocation, expected yields and a general farm input price index, α represents the coefficient of risk aversion and σ_R^2 the variance of farm revenue per ha depending on crop share; $\mathbf{A}$ and $\mathbf{b}$ are respectively the matrix of resource use per unit of quantity and the vector of right hand side value indicating either resource endowment or institutional bounds with associated shadow prices $\boldsymbol{\gamma}$.

[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 the impacts of family labour per ha on estimated farm specific efficiency parameters.

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 and simultaneously by taking the FOCs of the above model on the crop shares for each farm in each year the farm is observed. As we allow for non-binding constraints and the possibility to observe zero activity level of some crops on the farm, a set of Karush-Kuhn-Tucker (KKT) conditions represents the estimation framework (section 3.2).

3.1 Empirical model

Astonishingly, certain PMP applications set yield and price expectations equal to realized ones and this potentially leads to biased parameter estimates (Pope and Chavas, 1994). Estimating the expectation model in our framework would be overly complex, thus expected prices and yields enter as fixed and given in our estimation. We require a hypothesis on how price and yields expectations are formed at farm level and we opt for a partial adjustment approach for prices which yields expected prices equal to all the farms of the same sample in order to avoid endogeneity problems. Specifically, crop price expectations are formulated according to the adaptive expectation hypothesis (Chavas and Holt, 1990; Sckokai and Moro, 2006) using each sample's mean prices. Under this hypothesis the farmer makes an expectation at time t about the crop price at time $t+1$ based on the price observed at year t plus the mean error made in the last years' predictions if he had made a naive expectation. In order to aggregate individual crops to groups, we define Törnqvist price indeces on the expected prices. Yield expectations on the farm in a year are modelled by adjusting the crop sample average yield in that year by the ratio between the crop average yield observed on the farm and the sample average yield over those years where the crop is observed on that farm. Hence, differently from the expected prices, the expected yields are specific to each farm.

We introduce a dual quadratic cost function with one input which summarizes all costs reported in FADN besides those of renting land. The use of a quadratic cost function weakly relates our analysis to the PMP literature; however, we do not assume a Leontief relation between certain variable costs and acreage and our cost function depends on both crop shares (Heckelei and Britz, 2000) and expected yields, and not on acreages only. We assume that farmers apply a two-stage decision process where first expected yields are decided upon.[2] Furthermore, as advocated in Heckelei and Wolff (2003), the shadow prices of the constraints as well as the parameters of the cost function and those related to risk behaviour are simultaneously estimated by the set of KKT-type FOCs.

The quadratic part of the cost function, cq_{ft}, for farm *f* in year *t* is

$$cq_{ft} = \bar{\mathbf{x}}_{ft}{}'\mathbf{Q}_1\mathbf{yld}_{ft} + \bar{\mathbf{x}}_{ft}{}'\mathbf{Q}_2\mathbf{yld}^2_{ft} + \bar{\mathbf{x}}_{ft}{}'\mathbf{Q}_3\bar{\mathbf{s}}_{ft} \qquad (1)^3$$

where, $\mathbf{Q}$ are symmetric matrices of dimension $I \times I$, being I the number of crops grown in the area where the farm is located. Specifically, $\mathbf{Q_1}$ and $\mathbf{Q_2}$ are diagonal matrices of parameters which measure the linear and quadratic effect of expected yields on crop marginal costs while $\mathbf{Q_3}$ is a full matrix of parameters which accounts for own and cross effects of crop shares on crop marginal costs. $\bar{\mathbf{x}}$ and $\bar{\mathbf{s}}$ are the vectors of utility maximising expected output quantities and crop share averaged over three years. The farm average production quantities $\bar{\mathbf{x}}$ and crop acreages shares $\bar{\mathbf{s}}$ in a year are linear combinations of last, current and next year's production quantities and crop shares respectively; the linear combination over three years allows to capture potential crop rotational effects on the costs. The weights for the last and next year variables, $lagw$ and $leadw$, are endogenously estimated parameters:

$$\bar{x}_{fti} = \left(lagw\, x_{f(t-1)i} + x_{fti} + leadw\, x_{f(t+1)i}\right) \big/ \left(lagw + 1 + leadw\right) \qquad (2)$$

$$\bar{s}_{fti} = \left(lagw\, s_{f(t-1)i} + x_{fti} + leadw\, s_{f(t+1)i}\right) \big/ \left(lagw + 1 + leadw\right)$$

[2] Estimating an alternative model where yield decisions are endogenous did not yield satisfactory results. Already a simple visual comparison of the development of average yields, output and input prices index in the sample suggest that there is little relation between these. Modeling yield decisions at the single farm would require information on farm characteristics affecting the relation between input use and yields, such as soil type and micro-climate. Introducing a farm specific constant for each crop to capture the impact of such non-observable factors would potentially overfit the whole model as we have only between 5 and 7 observations per farm on average in each sample, 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.

According to (2), a change of the output x of crop i in the year $t-1$ or $t+1$ can impact current year's cost, e.g. by impacting on fertiliser or crop protection costs. The lag and lead parameters might also capture differences between the accounting period in FADN database and the actual cropping year. A Cholesky decomposition of $\mathbf{Q}_3$ ensures positive definiteness and hence convexity of the cost function with respect to the crop shares (Paris and Howitt, 1998). $\mathbf{Q}_3$ is hence expressed as a product between a lower triangular matrix and its transpose matrix, $\mathbf{LL}'$. The definiteness of the other matrices $\mathbf{Q}_1$ and $\mathbf{Q}_2$ is not required as yields are not treated as decision variables, thus marginal costs may decrease in crop yields. The latter cannot be excluded beforehand when e.g. soil and climatic properties are not controlled separately.

The linear part of the costs function consists of parameters which account for (1) fixed costs on the farm, $cfix$, (2) variable costs per unit of crop produced $\mathbf{cv}$ and (3) fixed costs per ha of land , ch, due to basic field operations:

$$cl_{ft} = cfix + \mathbf{cv}'\overline{\mathbf{x}_{\mathbf{ft}}} + ch\ L_{ft} \tag{3}$$

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 differences across farms.

As indicated above, in order to avoid scale effects, 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:

$$c_{ft} = \left[(cl_{ft} + cq_{ft}) * px_t * (1+\delta t) * cf_f \right] / L_{ft} \tag{4}$$

As we are not distinguishing between different inputs, the total marginal costs for producing a crop can be derived by taking the derivative of (4) towards the crop shares. Hence, the marginal cost of a crop depend on the constant term cv_i of that crop, on the expected yield of that crop according to the diagonal elements of Q_1 and Q_2, and on the crop share mix according to Q_3. In addition, they change from one year to another according to the product of px and (1+δt) while accounting for farm specific effects according to cf .

$$\frac{dc_{ft}}{ds_{fti}} = \left(cv_i + Q_{1ii} yld_{fti} + Q_{2ii} yld_{fti}^2 + \mathbf{Q}_{3i}' \bar{\mathbf{s}}_{ft} \right) px_t\ (1+\delta t)\ cf_f \tag{5}$$

The reader should note here some relevant differences to PMP applications. Firstly, the cost function in (4) and its derivative in (5) are driven by *crop shares* and not, as usual in PMP, by acreages. That avoids that marginal production costs increase linearly in farm size measured in hectares. Perhaps more important, there are no 'unobserved' costs in our model, (5) is an estimator of all accounting costs but land reported by the farms, the difference between revenues plus subsidies minus these costs defines the returns to land and to other binding constraints in the model, such as the set-aside requirement or production quotas.

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):

$$\sigma_R^2 = \frac{\mathbf{x'}}{L}\mathbf{V}_p\frac{\mathbf{x}}{L} + \mathbf{p'}\mathbf{V}_x\mathbf{p} + \sum_{i=1}^{5}\sum_{j=1}^{5} V_{p_{ij}} V_{x_{ij}} \qquad (6)$$

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 is computed from sample mean series of market prices over the period 1995-2008 after de-trending by the Consumer Price Index. The variance-covariance of crop yields is computed based on the farm level data in order to avoid the underestimation of yield variation due to the use of aggregate data (Just and Weninger, 1999). The farm level yields are de-trended by using the coefficient estimates derived from regressing each crop's regional yields on a quadratic trend and dropping the quadratic and even linear parameters if not significant; next, the farm level de-trended yields are subtracted by the crop mean yields specific for each farm; as a consequence, if the farm grows a crop only in one year, that farm does not contribute to the computation of the yield variance for that crop. Finally the de-trended and mean corrected yields are used to compute the variance-covariance matrix. We assume independence between crop price and yield variability; this assumption seems reasonable given that we mostly consider internationally traded crops (Serra et al., 2006).

The constraints of the programming model consists of a land balance (equation 7), compulsory set aside where applicable and sugar beet quotas.

$$\sum_i \mathbf{s}_{fti} \leq 1 \quad [\gamma] \qquad (7)$$

Finally, the expected output quantity in a year is defined from exogenous expected yield and endogenous acreage:

$$x_{fti} = s_{fti}\, L\, yld_{fti}$$

The FOCs for the farmer's optimal land allocation without accounting for set aside obligation and sugar beet quota are hence:

$$p_{ti} yld_{fti} \le \frac{dc_{ft}\left(\bar{\mathbf{s}}_{ft}, yld_{fti}, px\right)}{d(s_{fti})} + \frac{\alpha d\left[\sigma_R^2\left(\mathbf{s}_{ft}\right)\right]}{d(s_{fti})} + \gamma_{ft} \perp s_{fti} \ge 0 \qquad (8)$$

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.

3.2 Technical implementation of the estimator

The Cholesky decomposition, the cost function, the risk term and further elements make the estimation procedure highly non-linear. As we allow for (a) data constellations where the land rent drops to zero and not all land is used, (b) more set-aside land is present on the farm than legally required and (c) zero activity levels, the optimality conditions are KTTs, such that no closed form representation exists (see equation (8) above). Similarly to most PMP related estimation, we estimate in GAMS as standard econometric packages do not offer solvers for this class of estimation problems. We benefit from the so-called EMP (Extended Mathematical Programming, Ferris et al. 2009) package of GAMS which allows inter alia defining bi-level programming problems (Vicente and Calamai, 1994). Applications to water allocation problems based on EMP are included in Britz et al. (2013) and Kuhn et al. (2014). The estimation framework considers measurement errors on the allocated crop shares and on the total costs, but does not assume allocation errors of the farmer. In our bi-level programming setting, the outer optimization problem is the statistical estimator which searches for the optimal parameters to minimize the sum of squared error terms, while the inner optimization problems depicts the maximization of expected utility problems for each farm in each year the farm is observed at the given parameters and thus determines via the optimal crop allocation and resulting costs the error terms as a function of the given parameters. Specifically,

Outer problem

$$\min_{\boldsymbol{\theta},\alpha,lagw,leadw} \varepsilon = \frac{\sum_{f=1}^{F}\sum_{t=1}^{T}\sum_{i=1}^{I}\left(s_{fti} - s_{fti}^{obs}\right)^2 w_i}{\sum_{f=1}^{F}\sum_{t=1}^{T}\sum_{i=1}^{I}\left(s_{fti}^{obs} - s_{fti}^{SMobs}\right)^2} + \frac{\sum_{f=1}^{F}\sum_{t=1}^{T}\left(c_{ft}(\bar{\mathbf{s}}_{ft}, \mathbf{yld}_{ft}, px / \boldsymbol{\theta}) - c_{ft}^{obs}\right)^2}{\sum_{f=1}^{F}\sum_{t=1}^{T}\left(c_{ft}^{obs} - c_{ft}^{SMobs}\right)^2}$$

subject to

Inner problem

$$\max_{\mathbf{s}} EU_{ft} \big/ L_{ft} = E(\tilde{\mathbf{p}}_t\ \mathbf{yld}_{ft})'\mathbf{s}_{ft} + \mathbf{sub}'_{ft}\mathbf{s}_{ft} + dsub_{ft} - c(\bar{\mathbf{s}}_{ft}, E(\mathbf{yld}_{ft}), px/\boldsymbol{\theta}) - 0.5\alpha\boldsymbol{\sigma}_R^2\left(\mathbf{s}_{ft}\right)$$

subject to $\mathbf{As}_{ft} \leq \mathbf{b}_{ft}\big/L_{ft} \quad (\boldsymbol{\gamma})$

$$\bar{\mathbf{s}}_{ft} = lagw\,\mathbf{s}_{ft-1} + \mathbf{s}_{ft} + leadw\,\mathbf{s}_{ft+1}$$

$$\mathbf{0} \leq \mathbf{s}_{ft} \leq \mathbf{1}$$

where, the superscripts obs and $SMobs$ indicate observed values for each farm and the sample mean, respectively, w_i is a weighting factor which depends on the number of observations that grow crop i and $\boldsymbol{\theta}$ represents the cost function parameters. As stated previously, we assume stochastic disturbances on observed crop share and farm costs per hectare. The outer problem aims at minimising the sum of squared disturbances normalised by the corresponding total sum of squares by choosing $\boldsymbol{\theta}$, $lagw$, $leadw$ and α. The inner problem takes the parameters given by the outer problem and finds the farmer's crop share decisions maximising the farmer's expected utility subject to the constraints and it determines the disturbances as a function of the estimated parameters.

EMP automatically generates the FOCs of the inner problems, while GAMS offers transparent interfaces to performing Non-Linear Programming solvers such as CONOPT (Drud A. 1985 and 1992). As we estimate on unbalanced panels over many years, we have enough degrees of freedom to refrain from using a priori-information e.g. on supply elasticities.

The disadvantage of the estimation framework proposed by Heckelei and Wolff (2003) with inequality constraints and used by us is that test statistics on the parameters are hard to derive as derivatives of the estimated parameters cannot be calculated. An alternative is to optimize the behavioural model (inner problem) with perturbed estimates and report the changes in the fit criterion.

3.3 Corner solutions in crop choice

A problem with single farm data is the frequent occurrence of zero observations, in the PMP literature termed as the 'self selection problem' (Paris and Arfini, 2000). It is helpful to make a distinction between the case where the crop has been observed in one or several years on a farm, but is missing in others years and the case where the crop has never been observed on that farm. In the former, it is relatively straightforward to develop yield expectation for all years. In the latter, one option would be the use of correlations between regional yields reported in external sources.

In both cases, conceptually, in the absence of measurement errors, a zero observation implies that the marginal costs exceed marginal profits respectively utility. In order to yield perfect calibration in a PMP model, it is sufficient to introduce high enough marginal costs in the calibration point to drive the optimal acreage of non-observed crops to zero. However, the majority of authors in the PMP branch calibrate the model such that the marginal costs and revenue are equal at zero activity level for those non-observed crops; we do not see any good reason for doing that. Furthermore, as PMP type models require information on gross margins, yields and allocated costs which cannot be observed if a crop is missing for a farm, they typically use the sample mean for the missing observations. We judge that approach as hardly convincing as the most obvious reason why a farm does not grow a crop present in its region is that soil and climate conditions in that farm disfavour that crop compared to average regional conditions and they induce to lower than average yields or higher than average costs on that farm.

In our application we avoid the introduction of arbitrary yield information by ignoring crops in farms where they have never been observed. However, if a crop has been observed on a farm in one or several of the years, we estimate the farmer's crop expected yield for a year where the crop is not observed on the farm by multiplying the crop mean yield in the sample in that year by the ratio between the farm mean yield for the years where the crop is observed on the farm and the sample mean yield in those same years. The only difference to crops observed in all years is hence the number of observations underlying the mean calculations. Secondly, we introduce KKT-conditions such that the sum of the marginal costs with the marginal risk component exceed marginal revenue for zero observations. As a consequence, non-observed crops in a specific year contribute with less information to the overall estimator. In opposite, for observed crops, as long as positive acreages are estimated, the two terms are equal.

In our estimation we consider two model variants: the first model accounts for crops on a farm only in years where those crops are actually observed on that farm (Model 1), while the second model accounts for crops in all years the farm stay in the sample if they are observed at least in one year on that farm i.e. zero observations case (Model 2). The comparison between the two model variants allows judging the effect of the inclusion of the zero observations on the goodness of fit of the estimation, on the parameters estimates and on the supply elasticity.

4 DATA

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 farms which stay at least three consecutive years in the sample to gain information from previous and next year's crop shares. We focus on arable farms which produce cereals, oilseeds, sugar beet and, for Germany only, potatoes[4]. These crop categories represent the dominant production system in the regions under analysis. Farms producing specialty crops such as vegetables or rice are excluded from the analysis as their technology (e.g. land-man ratio) is rather different from the crops considered. We also exclude farms which are classified as specialized arable, but have some animals or produce fodder. Finally, we drop farms below 10 hectares and those where average total cost per hectare exceeds the revenue per hectare over the observation period. The data are from the FADN database, thus they are representing of commercial specialised arable farms of at least 10 hectares.

The final samples include 1,635 observations (the combinations of farms and years) in Northern Italy, 784 observations in Cologne-Aachen region and 1,565 in the French Grandes-Culture region (Table 1). The number of farms is 351, 125 and 218 respectively in each region. Hence, the French farms stay on average for a longer period (7.2 years) in the sample compared to Germans (6.2 years) and Italians (4.7 years). We group the crops grown on these farms into five crop categories: wheat, corn, other cereals, oilseeds and sugar beet; in Germany, potatoes are added. We also consider the set aside area, making a distinction between compulsory and voluntary set aside.

Italian farms are in average less diversified compared to the ones in Germany and France. The average number of crops grown on Italian farms in the sample is 2.3 and around 28% of the observations grow only one crop in a year. 17% of the farms even grow only one crop over the whole period they stay in the sample, 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 observations 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 grow only one crop. The average number of crops grown on the German farms in the sample is 3.2 and 3.8 in the French sample. These differences compared to the Italian sample may be partially explained by the larger average farm size of French and German farms, 95 and 123 hectares respectively, compared to 41 hectares for Italian ones. Indeed, the correlation coefficient between the number of crops grown on the farm and the

[4] The share of potato production in the other two regions is small and only a limited number of farms in the two samples grow potatoes.

Table 1. Descriptive statistics of the three samples

	Italy	Germany	France
Number of observations	1635	784.0	1565
Number of farms	351	125.0	218
Average number of crops grown on the farm	2.3	3.2	3.8
Observations that grow only one crop			
number	457	1.0	0.0
%	28.0	0.12	0.0
Farms that grow only one crop every year			
number	59	0.0	0.0
%	16.8	0.0	0.0

	Italy mean	Italy standard deviation	Italy observations number	Italy observations %	Germany mean	Germany standard deviation	Germany observations number	Germany observations %	France mean	France standard deviation	France observations number	France observations %
Crop share (%)												
Common wheat	11.6	18.5	677	41.4	47.1	14.3	777.0	99.1	48.9	11.3	1565	100.0
Corn	57.1	29.9	1505	92.0	0.1	1.4	13.0	1.7	3.8	6.9	525	33.5
Other cereals	3.4	11.7	217	13.3	14.9	12.0	625.0	79.7	15.9	12.1	1285	82.1
Oilseeds	14.1	19.5	807	49.4	2.4	5.4	171.0	21.8	21.7	11.0	1456	93.0
Sugar beet	7.0	11.5	567	34.7	24.5	8.3	775.0	98.9	9.5	9.5	1051	67.2
Potatoes	-	-	-	-	3.6	10.3	136.0	17.3	-	-	-	-
Fallow land set aside	7.0	4.8	1252	76.6	7.4	3.9	714.0	91.1	0.2	1.6	52	3.3
Farm size (ha)	41.4	51.3			95.4	53.1			123.2	63.1		
Family labour (units/ha)	1.2	0.6			1.2	0.4			1.2	0.4		
Hired labour (units/ha)	0.1	0.4	149	9.0	0.3	0.4	405.0	51.6	0.2	0.6	451	28.8
Total cost per hectare (euro/ha)	952.1	278.0			1168.0	337.8			865.9	183.6		

farm size over all the three samples together is 0.468 indicating the expected positive relationship between these two variables. In both the German and French samples, wheat has the highest share of farmland and it is grown in almost all farms. In Germany sugar beet has the second highest share crop, and is grown by almost all farms followed by other cereals, observed in 80% of the observations despite their low share. In France oilseeds takes the second place both in terms of share (21.7%) and in terms of adoption among farms (93%). A larger share of the French farms grows also other cereals and sugar beet besides wheat and oilseeds. The small share of fallow land set aside despite compulsory set-aside obligations on French farms is explained by the large adoption of non food crop set aside, which is included under the share of the corresponding crop.

Despite the considerable differences in farm size and similarity in crops grown, the average number of family working units per farm is around 1.2 in all the three samples. However, hired labour use differs: while it is employed in 9% of the Italian farms only, it is used in 29% of the French and in more than half of the German farms. The total costs per hectare, excluding land rents, is 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, by the large percentage of German farms that grow sugar beet and by the inclusion of potato cropping. However, if family labour was remunerated at the rate of hired one and included in the cost per hectare, especially Italian farms would experience a large increase in cost as they show the highest amount of family labour per hectare.

Time series data on regional yields used to de-trend the farm's expected yields for the computation of the covariance matrix are taken from the Eurostat database and, according to the availability of these data, they cover the time horizon middle of '80s-2008 for most crops. The covariance matrix of prices uses the sample mean of crop prices over the period 1995-2008 de-trended by the Consumer Price Index.

5 EMPIRICAL RESULTS

5.1 Goodness of fit and supply elasticities for Italy

Table 2 reports the goodness of fit of the two estimated models for the Italian sample: model 1 considers a crop on a farm only in years where it is actually observed, model 2 considers a crop on a farm in all years the farm stay in the sample if the crop has been observed at least in one year on that farm. The overall goodness of fit is measured by (1-ε)*100, while in the table we report each component of this overall fit. 1-ε hence represents the R^2 of a standard regression analysis. Although in our estimation we have only one farm specific parameter, the farm efficiency multiplier of the cost function, the R^2 of both the estimated crop shares and total farm costs in our Model 1 panel analysis is relatively high. That parameter contributes to the good fit for the costs per

Table 2. Values of each component of the overall goodness of fit (1-ε)*100 **in each sample**

	Model 1			Model 2		
	Italy	Germany	France	Italy	Germany	France
Crop share						
wheat	52.3	53.1	41.1	24.5	43.9	13.9
corn	77.6	20.9	25.9	53.3	30.6	23.3
other cereals	53.4	24.5	20.2	23.3	34.5	20.6
oilseeds	57.0	35.3	50.6	24.6	45.8	44.4
sugar beet	99.3	100.0	96.5	78.1	98.3	99.7
potatoes	-	27.7	-	-	17.3	-
Cost	73.4	48.0	64.3	64.3	48.2	71.1

Source: Own calculation

hectare, while the estimated crop shares are driven by the all costs function parameters. We estimate the fit for crop shares and not for the observed acreage, hence there is no artificial increase in the explanatory power by adding a land balance which helps to explain the variance in observed acreages and total cost. Indeed, if we consider the acreages instead of crop shares in the objective function of the outer problem, the R^2 of all crop acreages are close or above 90%. That point should be carefully considered if our results are compared to other studies.

If corner solutions in the yearly crop choices are considered (model 2), the fit for both crop shares and costs drops significantly. That is different from the French sample and might be linked to the fact that the average number of crops grown on Italian farms in the sample is smaller compared to the other two countries. When moving from model 1 to model 2, for most of the farms we add two or even more zero observations to each individual farm model which might outweigh the impact of the increased total sum of squares in crop shares. In addition, 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, but it does not indicate the degree of this divergence.

Table 3 reports the crop supply elasticities of Italian farms for the two models which are in a range similar to those found in other studies. In the first model all own supply elasticities are below 1. Besides sugar beet, whose production is subject to a quota, we find that the crop with the highest share in the sample, namely corn, has the lowest supply elasticities, which seems reasonable. All the cross supply elasticity are negative showing a substitution relationship between the crops considered. As expected, sugar beet shows the lowest substitution with other crops. The elasticities are higher in the zero observation case (Model 2) while all the crops show substitution relationship except other cereals with oilseeds.

The table also reports the reaction of selected key economic variables to a change in the crop prices. While the reaction of the expected utility, profit and revenue show the expected sign in model 1, the land rent on average in the sample seems to drop when the wheat price increases and all other prices are kept constant. This may be explained by the indirect effect of the wheat price increase on the risk term. The most grown crop, corn, leads to the highest change in the profit due to a price change. In some cases, we find profit decreases if a price increases, which is impossible in a profit optimization framework. However, under risk aversion behaviour, a crop expansion due to a price increase may lead to a drop in profit and to a reduction in the risk component. That effect is however very small (-0.01%) and only found for the second model where the risk aversion coefficient is higher (see also section 5.4 below).

Table 3. Elasticity of supply and elasticity of some economic variables with respect to crop prices in the Italian sample

	E(p) wheat	*E(p)* corn	*E(p)* othcer	*E(p)* oil	*E(p)* sbeet
share of wheat	0.86*	-0.81	-0.03	-0.17	-0.01
	2.45	-1.59	-0.11	-0.98	0.00
share of corn	-0.13	0.52	-0.02	-0.16	-0.01
	-0.22	0.73	-0.03	-0.20	-0.02
share of other cereals	-0.28	-1.02	0.62	-0.20	-0.04
	-1.01	-2.09	1.25	0.18	-0.06
share of oilseeds	-0.15	-0.81	-0.02	0.77	-0.01
	-0.83	-1.20	0.02	1.62	-0.01
share of sugar beet	-0.01	-0.06	0.00	-0.01	0.13
	0.00	-0.07	0.00	0.00	0.16
share of set aside	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
revenue	0.08	0.73	0.00	0.09	0.19
	0.07	0.81	-0.01	0.06	0.18

* The first row in each number block reports the elasticity of Model 1, while the second row reports the elasticity of Model 2.

5.2 Goodness of fit and supply elasticities for Germany

The fit of the estimated models for the German sample (see Table 2 above) is below the one found for Italy and the differences between the two model variants are smaller, and, in some cases, the fit even improves if zero observations are considered. The latter might reflect two combined effects of including missing observations: first, the total sum of squares of the observed 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 the dominating crop (92% of observations and 57% of farmland on average), average crop shares in our German sample are more balanced and the observed 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 Italians (4.7 years). The supply elasticities in the German sample (Table 4) show a similar pattern of

Table 4. Elasticity of supply and elasticity of some economic variables with respect to crop prices in the German sample

	E(p) wheat	*E(p)* corn	*E(p)* othcer	*E(p)* oil	*E(p)* sbeet	*E(p)* potatoes
share of wheat	0.43*	0.00	-0.20	-0.04	0.00	-0.03
	0.69	0.00	-0.40	0.00	0.00	0.00
share of corn	-0.47	1.28	-0.46	-0.08	0.00	-1.65
	-7.33	6.01	0.96	0.00	0.00	0.00
share of other cereals	-4.21	-0.01	4.17	0.00	0.00	-0.09
	-3.19	0.00	2.36	-0.04	0.00	0.00
share of oilseeds	-0.34	0.00	0.00	0.33	0.00	0.03
	-0.02	0.00	-0.06	0.12	0.00	-0.09
share of sugar beet	0.00	0.00	0.00	0.00	0.00	0.00
	0.00	0.00	0.00	0.00	0.04	0.00
share of potatoes	-0.09	-0.01	-0.02	0.01	0.00	0.47
	0.00	0.00	0.00	0.00	-0.04	0.06
share of set aside	-0.39	0.00	-0.31	-0.04	0.00	-0.02
	-0.13	0.00	-0.11	-0.01	0.00	0.00
land rent	0.47	0.00	0.39	0.13	0.00	0.09
	0.12	0.00	0.08	0.00	0.00	0.25
utility	0.74	0.00	0.03	0.08	0.91	0.25
	0.17	0.00	0.02	0.01	0.22	0.27
profit	0.74	0.00	0.03	0.08	0.91	0.25
	0.17	0.00	0.02	0.01	0.22	0.27
total costs	0.09	0.00	-0.01	0.00	0.00	0.05
	-0.24	0.00	0.09	0.00	0.00	-0.03
revenue	0.43	0.00	0.01	0.04	0.45	0.17
	0.32	0.00	0.00	0.02	0.32	0.40

* The first row in each number block reports the elasticity of Model 1, while the second row reports the elasticity of Model 2.

those of Italy: the dominating crop in the sample, wheat, exhibits a low supply elasticity, while corn, which has a low share in Germany, shows a higher value. The cross supply elasticities in model 1 indicate substitution relationships between most of the crops, while oilseed and potatoes are complements. Differently from Italy, where most of the crops are substitutes, some crops in the German sample show almost no relationship. Considering zero-observations has no uniform effects compared to Model 1: 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. Here, indeed, the zero value of the risk aversion coefficient avoids negative signs due to the trade off between expected profit and risk. Besides sugar beet whose production is under quota, the most grown crop in Germany, namely wheat, leads to the highest increase in profit as a consequence of a price change.

5.3 Goodness of fit and supply elasticities for France

The fit of the estimated models for the French sample (see Table 2 above) is worse than Italy for most crop shares but better than the Italian one for cost in model 2. Besides sugar beet, whose production is bounded by the quota, the two most frequent crops in France, wheat and oilseeds, show the lowest supply elasticities in both model variants, similar to the results found for Italy and Germany (Table 5). Sugar beet shows a negative sign for own price elasticity in model 2 and this may catch some distortion due to the production quota. The cross price elasticities for model 1 show that most crops are substitutes in the French sample. The elasticity of the expected utility, profit and revenues with respect to crop prices show a positive sign as expected. Surprisingly the land rent impact with respect to the prices of corn and other cereals, which are the less grown crops in the French sample, is negative.

Table 5. Elasticity of supply and elasticity of some economic variables with respect to crop prices in the French sample

	E(p) wheat	*E(p)* corn	*E(p)* othcer	*E(p)* oil	*E(p)* sbeet
share of wheat	0.59*	-0.04	-0.40	-0.09	-0.01
	0.19	0.00	-0.07	0.00	0.01
share of corn	-0.54	1.05	-0.22	-0.21	-0.01
	-0.21	0.92	-0.05	0.09	0.24
share of other cereals	-1.42	-0.06	1.52	-0.13	0.00
	-0.32	-0.08	0.47	0.02	-0.01
share of oilseeds	-0.23	-0.05	-0.10	0.34	-0.01
	0.00	0.07	0.10	0.46	0.06
share of sugar beet	-0.01	0.00	0.00	-0.01	0.08
	0.01	-0.25	-0.39	-0.77	-0.17

share of set aside	-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
revenue	0.46	0.04	0.11	0.15	0.25
	0.46	0.03	0.09	0.08	0.25

* The first row in each number block reports the elasticity of Model 1, while the second row reports the elasticity of Model 2.

5.4 Risk effects

It is worth to clarify the nature of the risk behavioural model underlying our analysis. As indicated in equation (6) and in the FOC in (8), we measure the trade-off between expected profit and risk on a per hectare basis. The optimal allocation expressed by crop share choices in equation (8) does not depend on farm size L, thus doubling the farm size 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 such that there is no wealth effect in our model.

The findings with regard to risk behaviour are country, and partly model dependent (Table 6). While our analysis suggests that risk consideration do not impact crop share decisions in German farms, Italian farms show a risk averse attitude, which implies that crop share decisions depend on the related market and production risk. The results for France are ambiguous: we find risk aversion only in the first model. We find a quite high risk aversion coefficient in model 1 in France, while it is estimated at zero in the second model.

[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, v, to all farms in the sample should leave our estimation results unchanged besides leading a different scaling of the risk aversion coefficient $\left[0.5\alpha\boldsymbol{\sigma}_R^2(\mathbf{s})\right]/v$. In addition, if we add the expected profit per hectare to the farmland value per hectare we end up with: $\left[0.5\alpha\boldsymbol{\sigma}_R^2(\mathbf{s})\right]/((v+E(\tilde{\mathbf{p}}\;\mathbf{yld})+\mathbf{sub}+dsub-c(\mathbf{s},E(\mathbf{yld}))$. However, this formulation leads probably to very similar results compared to the more simplified expression $\left[0.5\alpha\boldsymbol{\sigma}_R^2(\mathbf{s})\right]/v$ as the expected yearly profit is expected to be much lower than farm wealth and the amount of expected profit which remains after withdrawing for yearly farm household expenses and thus increases terminal wealth is small.

That estimation results might hint at some data problems: there had been e.g. subsidies under the Pillar 2 in France promoting the cropping of oilseeds which we could not include in our estimation, but they might influence the outcome. These findings might also be linked to average farm sizes: the larger farm size in Germany and France compared to Italy leads in average to a higher number of crops on a farm; thus, 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.

Our conclusion from these estimates is that diversification of crop shares probably plays a minor role as a risk management tool in specialized arable cropping. This might be supported by the observation that only the Italian sample whose farms show a rather high specialisation displays a coefficient different from zero in both models. We are also not certain if the method to define the covariance matrix for the yields is stable enough for a rotating panel with a limited number of observations per farm. The reader should note however that a well funded critique of the E-V model, namely that due to the quadratic functional form larger farms face a larger risk by definition, is not valid for our model which is estimated on a per ha basis.

5.5 Farm specific efficiency parameters

While our model assumes constant returns to scale within a farm imposed by the homogeneity of degree one of the cost function with respect to the farm acreages, it allows for efficiency differences across farms by the farm specific efficiency parameter of the cost function. The efficiency parameter could hence capture scale effects. In order to check whether the farm efficiency depends on farm size and family labour we regress the farm parameter of the cost function for Model 1 on farm size and farm's family labour per hectare. The results seem to indicate that the amount of family labour per hectare does not affect the total costs of the farm; this is quite surprisingly as we would expect that the higher the family labour per hectare employed on the farm, the lower the farm total costs per hectare should be due to substitution of hired labour. One reason could be poor data quality on family labour use, another one an indirect effect as small farms show a higher family labour per ha ratio.

The effect of farm size in hectares on the farm specific efficiency parameter is negative and significant at 10% significance level in the German sample, while it is positive and significant at 1% level in Italy and France (Table 6). However, the coefficients are in all cases quite small which might indicate that farm size has indeed a limited impact on costs on specialized arable farms. As average family labour use in the three samples is rather similar, profits per family annual working unit increase with farm size as long as the share of owned land stays constant, which underlines that structural change needs not necessarily to be driven by scale effects relating to accounting cost, but also by scale effects of (family) labour use.

Table 6. Estimates of the risk aversion coefficient and estimates of the regression of the farm efficiency parameter (cf_f) on farm size and family labour

		Italy	Germany	France
Risk aversion coefficient				
	model 1	0.0138	0.0000	0.0607
	model 2	0.0189	0.0000	0.0000
Parameter estimates of the regression of farm efficiency parameter cf_f (Model 1)				
farmland (ha)		0.0010***	-0.0012*	0.0013***
		-0.0003	-0.0007	-0.0004
family labour (units/ha)		-0.3706	0.0485	4.2037
		-0.7827	-0.1016	-4.2587
constant		0.9218***	1.1271***	0.5084***
		-0.0444	-0.1261	-0.0940

5.6 Lags and leads in crop shares and production quantities

The estimation of the effect of the last and next year crop choices on current year costs shows no or negligible small estimated 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 impact of the shares of previous and last year. Furthermore, as we need shares also for the first and last year of observation of each farm the lag (lead) observation drops out for the first (last) year of farm's observation and the weights for the remaining two years have to scale up to unity. 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 CONCLUSIONS

We present an estimation of the parameters of an expected utility programming model based on the FOCs and 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 are decided upon and next the optimal acreage allocation is chosen. We model only the second step, which allows us to exploit information on observed crop share decision and yields and to introduce an explicit land balance and institutional constraints in the estimation. The crop share variable in the cost function is a linear combination of previous, current and next year allocation in order to account for the cross year effects of crop allocation on costs. The risk component is introduced by accounting for both price and farm-level yield variance. The model is normalized by total farmland in order to avoid scale bias and such that crop shares are the decision variables. We use rotating panels of specialised arable farms in Northern Italy, the Cologne-Aachen Region in Germany and the Grandes-Culture Region in Northern France observed over the time period 1995-2008 and keep only farms which stay at least three consecutive years in the panels in order to gain information on cross year acreage allocation effect on cost function. We estimate by means of a bi-level programming approach which allows for non binding constraints and zero activity levels and we develop two model variants where zero activity levels are considered only in the second variant. The estimation results show a quite satisfactory fit for crop shares and costs with differences across the three regions and the two model variants. The values of the estimated supply elasticities are reasonable and, as expected, the crop with the highest share in each sample exhibits the lowest own price elasticity. The cross price elasticities indicate substitution relationship among most of the crops. The elasticity of land rent, utility, profit and revenue with respect to crop price exhibits a sign that is consistent with the expectation for most of the crops in each country.

The results on the farmer's risk aversion coefficient seem to indicate that the specialized arable crop farmers in our samples do not or to a limited degree use crop shares as an instrument of risk management. Indeed, measuring the risk attitude by crop allocation we find no aversion towards risk in Germany, aversion in Italy and ambiguous results for France. The aversion towards risk of Italian farmers leads them to employ diversification to stabilise their income only marginally as the Italian farms are the least diversified farms among the three countries considered. On the other side German (French) farms which has on average a higher number of crops grown on the farm do not show (do not show clearly) the use of crop diversification by means of risk management tool. We find a positive correlation between farm size and the number of crops grown on the farm, which is reasonable given that small farms usually manage one or two plots and the costs of dividing plots further might outweigh the gains from reducing risk by a more diversified crop portfolio. This may further support the argument that although Italian farms are risk averse they do not use crop diversification as a tool to manage risk. Indeed, given their average small size a diversification may lead to higher cost.

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 efficiency differences across farms. 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.

The results on the effect of last and next year crop choices on current year costs does not show cost reduction effect due to rotations. However, these results may underline a limited variation in crop shares across years hence we cannot conclude that crop rotations do not have a cost reducing effect. Further research may apply the setup proposed in this paper to plot level data in order to gain better information on crop rotations among plots and to improve the estimation of the potential cost reducing effect of crop rotations. In addition, when information on the allocation of variable inputs to crops is available it would be interesting to apply the approach developed in this paper to the estimation of a primal farm programming model.

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